STRUCTURAL EQUATION MODELING USING COMPLEX SURVEY DATA: EVALUATING QUASI-MAXIMUM LIKELIHOOD ESTIMATION WITH SATORRA-BENTLER CORRECTION AND MULTIPLE IMPUTATION

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Title of Study: STRUCTURAL EQUATION MODELING USING COMPLEX SURVEY DATA: EVALUATING QUASI-MAXIMUM LIKELIHOOD ESTIMATION WITH SATORRA-BENTLER CORRECTION AND MULTIPLE IMPUTATION

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Abstract: As a theory-guided approach, SEM can estimate directional pathways in complex models using longitudinal or cross-sectional data where randomized control trials would either be unethical or cost prohibitive, thereby providing researchers with an alternative approach for delineating causal relationships. As SEM is a technique requiring large sample size, federal and state level surveys are often used, which are designed with complex sampling strategies. As many of the variables and in turn, weighted-ness, may be subject to non-normality, it is important to adjust the SEM model fit statistics to more closely match the reference distribution (Satorra-Bentler, 1994). Further, missing data is a regular issue in nearly all surveys, especially those with large-scale, complex designs. The purpose of the study is to provide a comparison of estimations, modification indices, and goodness-of-fit tests for SEM between standard maximum likelihood estimation and quasi-maximum likelihood using Satorra-Bentler correction using a complex survey data and multiple imputation. Using non-simulated data with missingness can provide guidance on how to incorporate both SEM and multiple imputation in future research. This study found that coefficients were the same regardless of estimator; however, standard errors increased under QML. Model fit statistics were better under QML, and Lagrange multiplier values from the modification indices were on average lower under QML, however, only with structural model components.

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CHAPTER I

INTRODUCTION

1.1 Background

Structural equation modeling (SEM) is a statistical tool that combines latent constructs and measured variables through regression techniques. As a theory-guided approach, SEM can estimate directional pathways in complex models using longitudinal or cross-sectional data where randomized control trials would either be unethical or cost prohibitive, thereby providing researchers with an alternative approach for delineating causal relationships. SEM also allows mediating variables to hold their place between an exogenous variable and the endogenous variable, allowing for estimation of the direct and indirect effects on the outcome variable. The fit of the model is viewed as the comparison between the covariance matrix of a sample to the implied covariance matrix of the population. As SEM is a technique requiring large sample size, federal and state level surveys are often used.

Most of the large scale surveys conducted through US government agencies are designed with complex sampling strategies. Within these complex designs, methods of stratification and clustering are present in order to be efficient for both statistical and

practical efficiency. In these designs, primary sampling units (PSUs) are stratified in a multi-level aggregation to reduce variance among the variables of interest.

1.2 Statement of the Problem

Many issues arise in survey assessment which are often ignored, although they could, and often do, skew the research findings. Common problematic issues in survey assessment are non-normality in responses, as well as large differences in variable ranges. Further, ignoring sampling weights may have significant impact on normality, which is very important in both analysis and in generalization. Therefore, it is imperative to use appropriate adjustments when analyzing complex survey data.

Missing data is a regular issue in nearly all surveys, especially those with large-scale, complex designs. In previous decades, several methods have been used to analyze surveys with missingness; typically under unrealistic assumptions or causing extreme bias (Schafer & Graham, 2002). However, as computer power has increased, so have methods for handling missing data. While complete case analysis and mean-imputation still occur, other, more complex methods have evolved, e.g., full information maximum likelihood and multiple imputation strategies.

In SEM, model fit statistics should be adjusted to more closely match the reference distribution (Satorra-Bentler, 1994). Several studies have shown that quasi-maximum likelihood is preferable to maximum likelihood when using non-normally distributed multivariate data (Klein & Muthen, 2007, Moosbrugger, Schermelleh-Engel, Kelava, & Klein, 2009, Teo, & Khine, 2009). However, less research has been conducted on the differences between the two estimation methods using complex survey design in SEM. The specific problem is that there is little research investigating

the comparisons of coefficients, standard errors, and modification indices of structural equation modeling using the combination of current techniques to address the previously mentioned issues.

1.3 Purpose of the Study

The purpose of this study is to provide a comparison of estimations, modification indices, and goodness-of-fit statistics for SEM between standard maximum likelihood estimation (ML) and quasi-maximum likelihood using Satorra-Bentler correction (QML) with complex survey data. This quantitative analyses will model theoretical paths between latent and measured variables using real data with missing information. The outcome of the research is to distinguish the differences in outcomes in ML and QML estimation and provide a best practice approach to analyzing large data with missing information and complex survey design when using SEM and multiple imputations in future research.

1.4 Research Questions

SEM under complex survey design with missing data needs to be further explored to demonstrate the outcomes using ML and QML estimators. This study will compare the outcomes of model coefficients, standard errors, fit statistics, and modification indices under both estimators using complete case analysis, complete case analysis with complex survey design, and then with a modified dataset that has missingness in order to implement multiple imputation procedures.

Goodness-of-fit tests for models in SEM using QML with Satorra-Bentler correction have been explored in the literature; however, there still is uncertainty about how this procedure affects outcomes in complex data sets. Further, there is little

evidence to support or reject the use of multiple imputation in the presence of the Satorra-Bentler correction. With increased robustness for standard errors, this may attenuate the bias that can occur with multiple imputation.

Three research questions were addressed in this paper. The first question was, "How do ML and QML estimators affect SEM model-fit statistics when using variables with normal and non-normal distributions under normal conditions, under conditions of complex survey design, and then with multiple imputations?" The second question was, "How do the two estimators affect the modification indices produced by each of the SEM models?" The last question was, "When using survey data that has missing information in complex sampling design, does multiple imputation provide comparative coefficients?

The hypotheses of this paper are:

1. The estimations of goodness-of-fit statistics will improve with quasi-maximum likelihood and the Satorra-Bentler correction.
2. Modification indices of models under maximum likelihood and quasi-maximum likelihood with Satorra-Bentler correction will be similar.
3. Multiple imputation in a modified complete case dataset will provide similar coefficients to complete case analysis using quasi-maximum likelihood with Satorra-Bentler correction with complex survey design.

1.5 Nature of the Study

The study will merge three cycles of NHANES data, from 2005-2010, for analysis. Continuous, measured variables included in the study were age, serum cotinine levels, and food insecurity status. Cotinine was used as a measure of degree of current smoking status, and food security was measured using the Food Security Survey Module. Depression was constructed as a latent variable using a nine-item screener. Figure 1 shows the proposed SEM model that will be analyzed throughout this study.

Three pairs of models using this theoretical framework were constructed under increasing data complexity. Each pair consisted of a ML and QML with Satorra-Bentler correction estimated under the same data conditions. The first pair used complete case analysis with no survey design. The second pair used complete cases analysis and incorporated the NHANES survey design, while the third pair used the same dataset, which was modified to replicate missing information patterns that were present in the full NHANES data. This last pair of models used multiple imputation to address the missingness. Finally, two iterations of the model were analyzed using the full NHANES data to illustrate the appropriate best practices for SEM with complex survey design and missing data using quasi-maximum likelihood estimation with Satorra-Bentler correction and multiple imputation. The first iteration was used to compare full data under QML with imputations to the previous pairs of models in order to demonstrate issues when using complete case analysis. The second iteration was to produce the most appropriate model using best practices of QML with Satorra-Bentler correction, multiple imputation, and appropriate model respecification.

1.6 Significance of the Study

The novel contributions this paper makes to the field are to provide a comparison of results between maximum likelihood SEM and quasi-maximum likelihood with Satorra-Bentler correction. More specifically, and as noted by Bollen, Tueller, and Oberski (2013), there is no literature regarding the comparison of modification indices provided by each method when using complex survey data. There is also no research reporting differences of SEM estimators using multiple imputation under the conditions previously described. Further, these strategies were investigated using NHANES data to provide future reference for using SEM with complex surveys and methods for handling missing data therein.

CHAPTER II

LITERATURE REVIEW

2.1 Structural Equation Modeling

Structural equation modeling (SEM) is becoming more and more popular in social sciences as an efficient way to model complex relationship using multivariate data. SEM is considered to be a grouping of techniques that includes path analysis and factor analysis. SEM is both versatile and functional in that it can incorporate categorical variables, measured variables, and latent variables. Latent variables are measured through factor analysis, a procedure that measures an unobservable construct through multiple observable measures and is referred to as the measurement model of SEM. Path analysis is referred to as the structural model in SEM. Path analysis, based on covariances, connects variables in the model and provides the significance and amplitude of their theorized relationships. Graphical representations of SEM are referred to as path diagrams. These diagrams usually include the variables, their pathways, standardized or unstandardized coefficients, standard errors, and significance. While the individual pathways are often of importance, the primary concern is how well the data fits the conceptualized model. The objective of SEM is "to determine the goodness-of-fit

between the hypothesized model and the sample data" (Byrne, 2013). Many statistics are offered in current software to assess *goodness-of-fit*, as well as solutions to improve them.

2.1.1 Estimation and Model Fit.

Model fit is a determination of how well data fits with a theoretical model. Model fit is determined through solving equations so that the data equals the model plus an error term, which is similar to multiple regression. However, in the case of SEM, the model has many components to estimate, and through advances in computer software, has become much easier to accomplish. Maximum likelihood is the most common method of SEM estimation. The second type of estimation to be used in this study is the quasi-maximum likelihood method with Satorra-Bentler correction.

Maximum likelihood estimation. Maximum likelihood estimation has been described in detail elsewhere (Myung, 2003; Ferron & Hess, 2007); however, to compare ML to QML, an abbreviated baseline should be established. The ML approach starts with probability density functions for each observation and estimates a likelihood function. The likelihood function can be considered as a simultaneous joint distribution on all observations (Myung, 2003). Iterations of the likelihood function continue from a starting guess until the maximum likelihood function converges for a model. A sample likelihood function can be written as:

$$L(X|\mu,\Sigma) = L = (2\pi) - \frac{Np}{2}|\Sigma| - \frac{N}{2}exp\left[\sum_{i=1}^{N} - \frac{(X_i^T - \mu)^T\Sigma^{-1}(X_i^T - \mu)}{2}\right] \quad 2.1$$

where μ is one mean vector, Σ is one covariance matrix and X is the data. The goal of ML is to maximize the function by finding the best fitting value of μ and Σ.

ML is the default method of estimation in statistical software that handles SEM. Generally, ML is consistent in producing true values as the sample size gets larger and is considered efficient, with typically smaller standard errors than other estimation techniques when assumptions are met. ML requires relatively large sample sizes, and while there are varied recommendations, a generally accepted minimum is 200 observations (Kline, 2016).

Assumptions for ML, in addition to a large sample size, are that the indicator variables should be continuous and multivariate-normally distributed. As noted by Garson (2015), ML can handle ordinal data when there are at least five ordered categories and when common values of accepted skewness and kurtosis levels of normality are between +/- 1.5. Additionally, the sample must be independently and identically distributed. Issues with ML arise when these assumptions are not met, mainly that error variances may be underestimated (Garson 2015).

Quasi-maximum likelihood estimation. Quasi-maximum likelihood estimation was developed for use with SEM with non-normally distributed variables and higher order effects (Klein and Muthèn, 2007). The specific calculations of QML estimations (White, 1982) and QML techniques with regard to SEM are fully described elsewhere (Klein & Muthèn, 2006; Klein & Muthèn, 2007). The goal of QML is to maximize a quasi-log-likelihood function using an approximated non-normal density function (Klein & Muthèn 2006). As this method only approximates the log-likelihood function, it may

provide less efficiency (Klein & Muthèn, 2007); however, as opposed to ML, it is more robust to violations of the assumptions that are required for ML. While important for both ML and QML estimations, theory must guide the model, and misspecification can lead to erroneous results (White, 1982).

Satorra-Bentler correction. The Satorra-Bentler correction is a correction for maximum likelihood estimation in that it relaxes the assumption for multivariate normal data, therefore creating robustness to non-normal distributions and providing both a better chi-square goodness-of fit statistic and better estimates of other common "fit" indices. The Satorra-Bentler correction is a sandwich estimator, meaning it uses partial first order derivatives to correct for the partial second derivatives and is explained in detail elsewhere (Carroll, Ruppert, Stefanski, & Crainiceanu, 2006). It also corrects for heteroscedasticity, adjusting standard errors. Klein, & Muthén (2007) and Oberski (2014) suggest QML with the Satorra-Bentler correction is most appropriate for complex survey analysis due to the correction for standard errors.

2.1.2 Model Fit Indices

Chi-Square Test. The ML function is commonly transformed to the log-likelihood function and can be used to test competing models- mainly the unstructured covariance matrix against the theorized. The Chi-square test statistic is calculated by finding the difference of the log-likelihood values between the unstructured (H_0) and model implied (H_1) covariance matrices, multiplied by -2:

$$X^2 = -2(\log LH_0 - \log LH_1) \quad 2.2$$

This test is also be referred to as the -2 log likelihood (-2LL) test and is used as a base value for the Akaike and Bayesian Information Criterion (AIC and BIC, respectively). Comparing AIC and BIC between models can show which model, having a lower value, is a better fit.

As a measure of absolute fit, or the ability to closely reflect the observed covariance matrix, the Chi-square test is very conservative; therefore it is susceptible to large sample sizes, and in turn, will produce a significant p-value when in fact there is good model fit. Due to the extreme sensitivity of this test when using large samples, other tests of absolute fit have been developed such as the Root Mean Square Error of Approximation and Root Mean Square Residual. Additionally incremental fit indices, such as the Comparative Fit Index and the Tucker-Lewis Index are also useful.

Root Mean Square Error of Approximation. The Root Mean Square Error of Approximation (RMSEA) is generally regarded as a good measure of model fit and does not require a comparison to the null model. It is calculated as follows:

$$\sqrt{(X^2 - DF)}/\sqrt{DF * (n-1)} \qquad 2.3$$

where *n* is the sample size, *DF* is the degrees of freedom, and X^2 is the value of the theorized model's chi-square (Garson 2015). Given that the formula includes the degrees of freedom and sample size, it is beneficial to have a large sample size, and incurs penalty for increased model complexity (i.e., higher degrees of freedom). Interpretation of the RMSEA is generally two-fold. The value of the RMSEA should be less than 0.1 to assume reasonable fit, while less than 0.05 indicates good fit (Kline, 2015). The p-value associated with the RMSEA should be non-significant, as it is testing for model

difference between the null and theorized models. The second part of interpretation for the RMSEA involves the calculated confidence intervals. Since the value of the RMSEA should be below the cutoff of 0.1, the lower bound confidence interval should be close to zero, while the upper bound confidence interval should be less than 0.1 to be considered a good fit (Garson, 2015).

Standardized Root Mean Square Residual. The Standardized Root Mean Square Residual (SRMR) is the standardized mean difference between the predicted and observed covariance matrices, based on their residuals. This measure assumes that the sample is large enough to ensure the stability of the standard error; however, it may be lower when there are very large samples size or highly complex models (Garson, 2015). Typical ranges for cutoff criteria are less than 0.1 for acceptable fit with lower numbers representing better fit; however, Kline (2016) recommends reporting individual or patterned trends in the residual correlation matrix.

Incremental fit measures. Measure of incremental fit, such as the Comparative Fit Index (CFI) and the Tucker-Lewis Index (TLI), are comparative measures of the researcher's theorized model against the null model representing the worst fit possible. These measures have been well researched for the ability to judge model fit (Bentler, 1990, Bentler & Bonnet, 1980, Hu, & Bentler, 1999). These two indices are highly correlated but may have slightly different values due to their respective calculations:

$$\text{CFI} = 1 - \frac{(X^2 - DF)_{nm}}{(X^2 - DF)_{rm}} \quad 2.4$$

$$\text{TLI} = \frac{(X^2/DF)_{nm} - (X^2/DF)_{rm}}{(X^2/DF)_{rm} - 1} \quad 2.5$$

where *nm* = null model and *rm* = researcher model (Mehmetoglu, & Jakobsen, 2016). The TLI has a greater penalty for model complexity as can be seen in the calculations above. Values for the CFI and TLI are considered good when they are above 0.9; a figure "which indicates 90% of the covariance matrix can be reproduced by the model" (Garson, 2015, p. 66). Other incremental tests are available, but not highly recommended. Reporting of either the TLI or CFI is generally accepted in addition to the absolute measures of fit: the Chi-square test and the RMSEA.

2.1.3 Modification Indices.

As an integral component of this research is to compare modification indices produced through different SEM estimation techniques, the study must consider how the values of a modification index are calculated and what the recommendations are for use. Modification indices provide information regarding path coefficients and covariances that were constrained or excluded from the model. The calculation of change is more specifically known as a univariate Lagrange multiplier test. From this test, a larger value produced for a pair of variables indicates a greater potential to improve the model fit function. In SEM, the Lagrange multiplier uses an algorhythm to estimate the change in the Chi-square value of the fitted model with one degree of freedom if a particular path were to change from fixed at zero to becoming freely estimated (Kline, 2016).

Generally, modification indices are assessed to find instances of poor fit in a model, allowing the researcher to identify post-hoc adjustments to the model parameters, so long as guided by theory. However, especially with small samples, the indices follow patterns of the data and empirical modification may not lead to a reproducible model

(MacCallum 1986; Silvia & MacCallum 1988). This study compared the modification indices between ML and QML estimations under varying levels of data complexity.

2.2 Missing Data

Missing data occurs in nearly every form of survey research and when mishandled can lead to biased estimates and distributions, incorrect standard errors, and potentially incorrect results (Stuart, 2015). When confronted with missing data, the researcher must first determine if the missingness is ignorable or non-ignorable, which must be estimated by looking at other variables within the data set (Sijtsma & Van der Ark 2003). Ignorable data follows no pattern with regard to the other items of the survey nor to any demographic or other possible explanatory variable within the experimenters design. This type of missingness is generally referred to as missing completely at random (MCAR). Sijtsma and Van der Ark (2003) explain that in a large sample, where missing data is MCAR, complete case analysis (list-wise deletion) may be acceptable with the tradeoff of lower statistical accuracy and power, but with unbiased parameter estimates. Complete case analysis has been shown to cause moderate to severe implications even in large data sets, but it intensifies when the sample is small. If the missing data is dependent upon other variables in the data, but not of the item itself and not explained by external factors, it is classified as missing at random (MAR) (Little & Rubin, 2002). Lastly, if missing data depends on an unobserved predictor or on the variable itself, it is not missing at random (NMAR), and the missingness must be either modeled, which is imprecise and difficult, or acknowledged as a source of bias in the interpretation of the study's findings.

Simple imputation strategies, such as mean imputation, last observation carried forward, and hot-deck imputation strategies, can provide the researcher with a full data-set, but may either artificially reduce variability or yield results that are much more precise than they should be or both, leading to inflated type I error rates (Li, Stuart, & Allison, 2015). Mean imputation is substituting the average value of the variable for each missing value which in turn reduces the variable's variance. This can be very problematic, as it systematically reduces variance in the data and artificially supports a normal distribution. Last observation carried forward (LOCF) is a method used in longitudinal studies when there is dropout (Gelman, & Hill, 2006). An example of a problematic issue with this method occurs when tracking chronic disease states; using LOCF may attenuate the trend of progression and increase prognosis or life expectancy. Hot-deck imputation involves borrowing responses from other observations of the variable, a process which allows only for plausible values to be included and which can be matched appropriately. Weaknesses of this technique include difficulty in finding appropriate matches in small studies, not capturing values that may be more extreme than are currently in the dataset, and possibly reducing variance (Andridge & Little, 2010).

Techniques such as the expectation-maximization (EM) algorhythm and full-information maximum likelihood (FIML) are ways of using an incomplete dataset that infer a solution utilizing the available information of the other variables. These are technically not imputation strategies, but have been studied to perform well in situations with missing data. Conversely, these techniques are not currently supported by software in the presence of complex survey data. In the circumstance of SEM with complex survey

designs that require weighting, only multiple imputation is currently supported by software to account for missing data.

2.2.1 Multiple Imputation

Multiple imputation (MI) is a way to incorporate missing values to complete a dataset, or rather multiple datasets, each computed independently under a Bayesian model that includes uncertainty about the missing data (Rubin, 1987, Schafer, 1997; Little & Rubin, 2002). The datasets are analyzed individually and then combined to give appropriate output using a set of rules developed by Rubin (1987). The combined procedure produces more accurate standard errors than the previously mentioned imputation methods (Greenland, & Finkle, 1995; Vach, & Blettner, 1991). Assumptions for standard multivariate-normal multiple imputation (MVN-MI) procedures assume a joint model for all variables included in a model, as well as univariate normal distributions or, in the case of multivariate analysis, multivariate normality (Schafer, 1997; Little & Rubin, 2002). More flexibility can be achieved when using multiple imputations with chained equations (MICE). This allows data to be imputed for each variable in a stepwise fashion, accommodating different distribution types- Poisson, logistic, or Gaussian (Raghunathan, Lepkowski, Van Hoewyk, & Solenberger, 2001). Auxiliary variables, which are additional variables that are not part of the analysis of interest but are correlated with the variables of missingness or are predictive of missingness, can be used in the MI process to increase the validity of the imputed data.

The number of imputations needed for analysis may vary based on the complexity of the model and the amount of data that is missing (Bodner, 2008; Graham, Olchowski and Gilreath, 2007). Generally, the minimum suggested number of imputations is five;

however, more have been shown to increase accuracy of results (Bodner, 2008). The fraction of missing information (FMI) can be calculated using the imputations' degrees of freedom and estimates of standard error after the analysis is completed (Graham, 2012) as:

$$U = \Sigma SE^2/m \tag{2.6}$$

$$B = \Sigma S_p^2 \tag{2.7}$$

$$df = (m-1) = \left[1 + \frac{U}{(1+m^{-1})B}\right]^2 \tag{2.8}$$

$$FMI = \frac{\left(\frac{(1+m^{-1})B}{U}\right)+2/(df+3)}{\left(\frac{(1+m^{-1})B}{U}\right)+1} \tag{2.9}$$

where *U* is the within variance component, *B* is the between variance component, and *m* is the number of multiple imputations performed. The FMI is useful in determining the number of imputations that would be appropriate, which researchers suggest should be 100 times the FMI (Graham, Olchowski and Gilreath, 2007; Stuart, 2015; Li, Stuart, & Allison, 2015; StataCorp, 2015).

2.3 Complex Survey Data: NHANES

The National Health and Nutrition Examination Survey (NHANES) uses a complex sampling strategy to represent the noninstitutionalized civilian population of the US. NHANES uses a four-stage sampling design, where the PSU is the county, which is then segmented into counties, then dwelling units, and finally selection of individuals

within the household. NHANES oversamples certain subgroups of the US population to obtain more reflective measures of those groups. During the 2005–2006 cycle, 10,348 participants were interviewed, and 9,950 completed the examination (Johnson, Paulose-Ram, Ogden, Carroll, Kruszan-Moran, Dohrmann, et. al, 2013).

According to Johnson, et al., (2013), sample weights assigned to each participant represent the number of persons in the United States based on their subgroup. Subgroups that were over-sampled from the population during the chosen cycle were non-Hispanic Black persons, Mexican-American persons, low-income White persons, persons aged 70 and over, and adolescents aged 12–19 for the interview.

The weighting of the interview and examination procedures are described in detail elsewhere (Johnson, et al, 2013); but the calculations for the final weights for the interview are:

2.10

$$w_{i(I)} = w_{i(Base)} f_{i(NR,S)} f_{i(TR,S)} f_{i(PS,S)} f_{i(NR,I)} f_{i(TR,I)} f_{i(PS,I)}$$

and for the examination:

$$w_{i(E)} = w_{i(Base)} f_{i(NR,S)} f_{i(TR,S)} f_{i(PS,S)} f_{i(NR,I)} f_{i(TR,I)} f_{i(PS,I)} f_{i(NR,E)} f_{i(TR,E)} f_{i(PS,E)} \quad 2.11$$

where *w* is weight, *I* indicates interview, *Base* is the base weight, *f* is factor, *NR* is non-response, *TR* is trimming, *PS* is post-stratification, and *E* indicates examination.

The Center for Disease Control and prevention (CDC) acknowledges that NHANES data in individual cycles are limited in generalization capability. Each year, only approximately 15 primary sampling units are selected from throughout the United States. From these PSUs, only about 5,500 to 6,000 persons are selected for participation.

While this dataset is nationally representative, the relative sample is small and needs additional variance adjustments through linearization, which is included in most software designed for use with complex survey designs. Merging more than one cycle is recommended but requires appropriate adjustment of the annual sampling weights.

2.4 Model Theory: Food Insecurity, Depression, Smoking, and Age

Food insecurity, a household level condition of limited or uncertain access to adequate food supply, is increasingly recognized by public health stakeholders for its health, economic, and social implications (USDA, 2017). Nutritional deprivation, even in acute situations, can cause deviations in mood and behavior (Slade & Bharadwaj, 2010). Research has shown that both macro- and micronutrient deficiencies are risk factors for altered psychological function and mood states, and it is likely they are often found together (Liu, Zhao, & Reyes, 2015).

Additionally, food insecure individuals are often at an increased risk for other chronic diseases such as diabetes and cardiovascular disease and in turn may be forced to choose between providing food for themselves and their families or buying the medication they need to stay well (Seligman, Laraia, & Kushel, 2010). The lack of being able to provide for oneself and family may lead to the erosion of self-efficacy and independence that over time may lead to symptoms of depression (Carter, Kruse, Blakely, & Collings, 2011). Conditions associated with food insecurity (such as illness, injury, unemployment, underemployment, prior poor decisions, and family changes) are typically accompanied by negative emotional responses such as sadness and depression (De Marco, Thorburn, & Kue, 2009).

Food insecurity can be viewed as a predictor of depression when combining evidence and theory. Data from longitudinal studies in which the measure of food insufficiency was correlated with depression at both baseline and yearly follow-ups predicted depressive symptoms in the second year. Respondents who experienced food insufficiency at both measures were more likely to have Major Depressive Disorder and to lack *mastery*, the perception of not having control of their lives. Participants who reported food insufficiency only in the second year, met the criteria for recent major depression (Siefert, Heflin, Corcoran, & Williams, 2004).

Additionally, smoking, as a coping mechanism, occurs more often in lower income households (Armour, Pitts, & Lee, 2008). Separately, research has shown that persons experiencing major depressive disorder are more likely to have a history of smoking as well as be less likely to be successful in cessation (Breslau & Peterson, 1996). The combination of depression and food insecurity may influence a person to increase smoking behavior.

Smoking cessation attempts have been shown to increase in older age groups (CDC, 2011), making it likely that cotinine levels would decrease with age. Increasing age has also been associated with a decrease in food security in several countries (Arene & Anyaeji, 2010; Mango, Zamasiya, Makate, Nyikahadzoi, & Siziba, 2014; Zhou, Shah, Ali, Ahmad, Din, & Ilyas, 2017); however, no study has supported this in the United States. The current study will explore the direct relationships of age and food security, depression and smoking, while exploring other direct and indirect effects of these variables within the US population, as shown in Figure 1.

CHAPTER III

METHODOLOGY

This study is a non-experimental, secondary analysis using cross-sectional data from the National Health and Nutrition Examination Survey (NHANES) to examine theoretical pathways linking measured variables and latent constructs. NHANES is a nationwide study to assess the health and nutritional status of the US population using a number of instruments, including interviews, questionnaires, and physical examinations. NHANES data (CDC, 2010) is collected in two-year cycles, with the present study merging three cycles from 2005-2010. Analyses in this study were conducted with R (R Core Team, 2017) and R Studio (R Studio Team, 2015) using select packages.

3.1 Demographics

Participants. The sample taken from the 2005-2010 NHANES cycles was comprised of subjects over the age of 20 who completed the interview and examination. Using the R package *psych* (Revelle, 2017), the sample's range, mean, and median for age were summarized. Adding the complex survey design, the populations weighted mean for age was also calculated using the survey package (Lumley, 2017). Gender

and race were assessed as a percentage of the sample and population as well.

Weighting. Full weighting for the interviews and examinations for survey participants were applied as necessary. The researcher will account for the complex sampling design by using variance estimates for clustering in groups at both strata and PSU levels. NHANES masked these variables in efforts to maintain participant confidentiality. This study will use the weightings provided from the Mobile Examination Center (MEC) and will combine three cycles of data, thus weighting estimates per observation will be reduced by one-third.

3.2 Measures

The present study used data collected from NHANES validated questionnaires and measures from among 15 sampling sites around the nation. Measures incorporated into the model were the FSSM household food security score, the Depression Screener (DPQ), age, and the lab measure of cotinine, which has been validated as a measure of current smoking status (Vartiainen, Seppälä, Lillsunde, & Puska, 2002). Measures in the model were selected for two reasons: they are supported by theory as required for SEM, and they each have unique scales and distributions that were evaluated for univariate normality.

Household Food Security. The Food Security Survey Module (FSSM), provided in Appendix B, covers a variety of areas relating to lack of adequate food and receipt of food assistance in various forms. This questionnaire consists of 10 items and provides insight on the degree of food insecurity within a household. Participants respond to the items based on seven frequency choices (Yes, Often, Sometimes, Almost every month,

some months but not every month, Only 1 or 2 months, or No). The responses are collapsed into a dichotomous categorical variable (1 or 0) with the first five responses coded as 1 and the remaining 2 coded as 0 (USDA ERS, 2012). The NHANES data has a different coding mechanism; therefore, this data will be transformed to binary scoring as intended. For the 10 item assessment, each question answered affirmatively receives 1 point, resulting in a continuous score ranging from 1 to 10; however, benchmark scores are used to assign four levels of food security. The four categories are: 1) *High food security* (score of 0-2)- meaning that individuals within the household have no issues with access to food or worry about acquisition; 2) *Marginal food security* (3-5)- involving marginal food security where one to two indicators were reported, which often relate to anxiety or worry, but no reported changes in food consumption; 3) *Low food security* (6-8)- involving a restriction of variety or limited access to healthy food with possible food shortages that may require eating less than usual; and 4) *Very low food security* (9-10)- where food shortages and skipping meals lead to malnourishment and inadequate food consumption (USDA ERS, 2017). The sum score from 1 to 10 will be used in the SEM analysis.

Depression. The Patient Health Questionnaire (DPQ), provided in Appendix C, is a screening instrument used to determine depressive symptoms occurring in the previous two weeks; it consists of nine items (Figure 2). The scale was developed by Kroenke, Spitzer, and Williams (1999) and will be used to assess depression in this model. The DPQ is taken from the NHANES Patient Health Questionnaire section, which is a rendition of the Prime-MD diagnostic instrument (CDC, 2006). Each question is rated on a Likert scale from 0, meaning not at all, to 3, meaning nearly every day. The nine items

are based on signs and symptoms of depression from the fourth edition of the Diagnostic and Statistical Manual of Mental Disorders. Depression severity can be defined by several cut points from the total score that ranges from 0-27 (Kroenke, Spitzer, & Williams, 2001).

3.3 Methods

Using complete case data, a confirmatory factor analysis (CFA) was produced with ML using the package *lavaan* (Rosseel, 2012) to ensure the DPQ depression screener retained its integrity as previously validated (Kroenke, Spitzer, & Williams, 1999). Items were checked to determine that all had factor loadings greater than 0.300. Composite reliability was calculated to determine overall reliability of the scale among the participants.

Each variable's missingness was computed from the full NHANES dataset. The full NHANES dataset with and without weightings and the complete case dataset were broken down by age group, race, and food security status to compare the percentage of completion of the survey components. Figures of these patterns were generated with the R package *VIM* (Kowarik, & Templ, 2016). These patterns helped to determine whether the incomplete information is missing completely at random (MCAR), missing at random (MAR), or not missing at random (NMAR) based upon age, race, or food security status.

In this study, Eight SEM models were estimated based on established relationship as shown in Figure 1. The first and second models were conducted using ML estimation and QML with the Satorra-Bentler correction with complete-case observations using the l*avaan* (Rosseel, 2012). The next two renditions of the models also used the complete

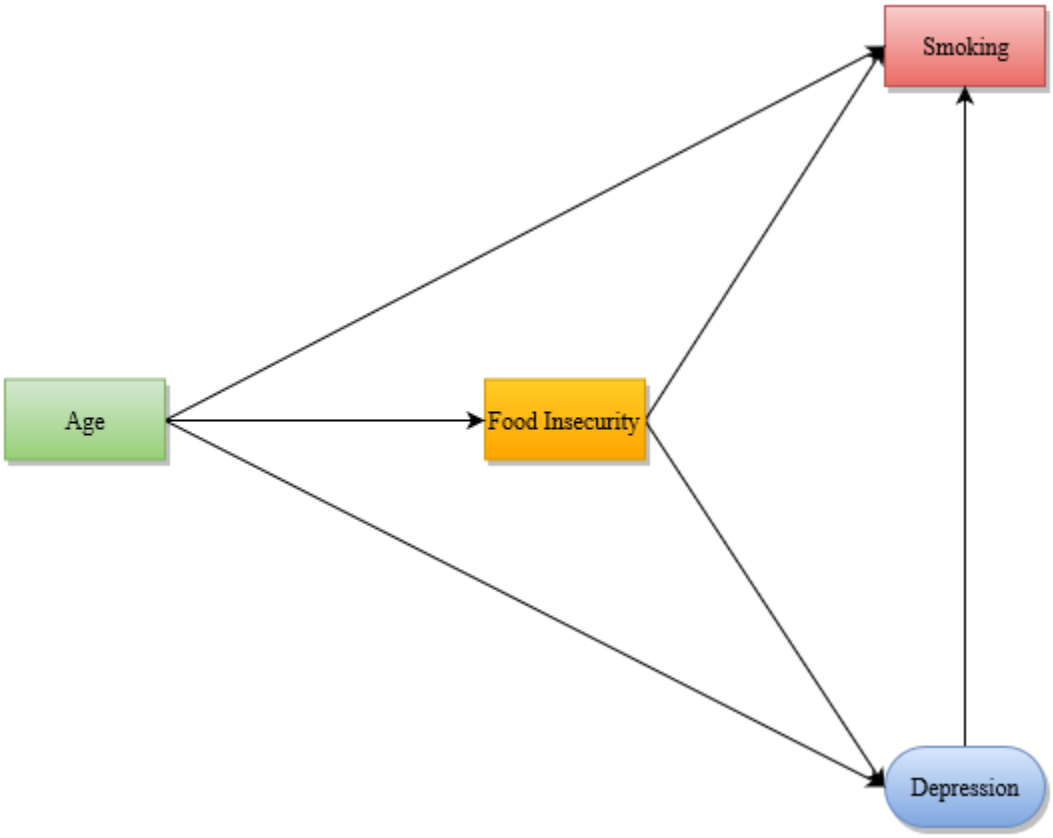

Figure 1. Theorized structural equation model of the relationship between Age and Smoking with mediating factors of Food Security and Depression.

cases, but incorporated the complex survey design of NHANES under ML and QML using the R packages *survey* (Lumley, 2017) to add the survey design and weighting and *Lavaan.Survey* (Oberski, 2014) to combine the model and design. Full coding is provided in Appendix E.

Next, the complete-case dataset was modified to match the missingness from the full NHANES dataset. To do this, the data set was split into five subsets by race. Within these subsets, participant information was sorted randomly, and the percentage of missingness from the Full NHANES dataset was deleted for the DPQ depression screener variable. The observations were then re-randomized and had the relevant percentage of observations deleted for each of the next variables- cotinine and food security score. This process was repeated for each of the split data subsets before they were rejoined as one. Multiple imputations were generated using the *mice* (van Buuren, & Groothuis-Oudshoorn, 2011) and *mitools* (Lumley, 2014) packages to account for the missing information in the dataset.

The final outputs were compared based on conservativeness for variance and standard error estimates as well as -2LL, BIC, AIC values. Goodness-of-fit indices were used to determine how well the data fits the model under each circumstance using ML and QML. Modification indices were compared by subtracting the value of the estimated parameter change provided by the LaGrange multiplier in each subsequent model from the initial ML model and presented as a percentage of change. The final two models were constructed using the full NHANES dataset and multiple imputation.

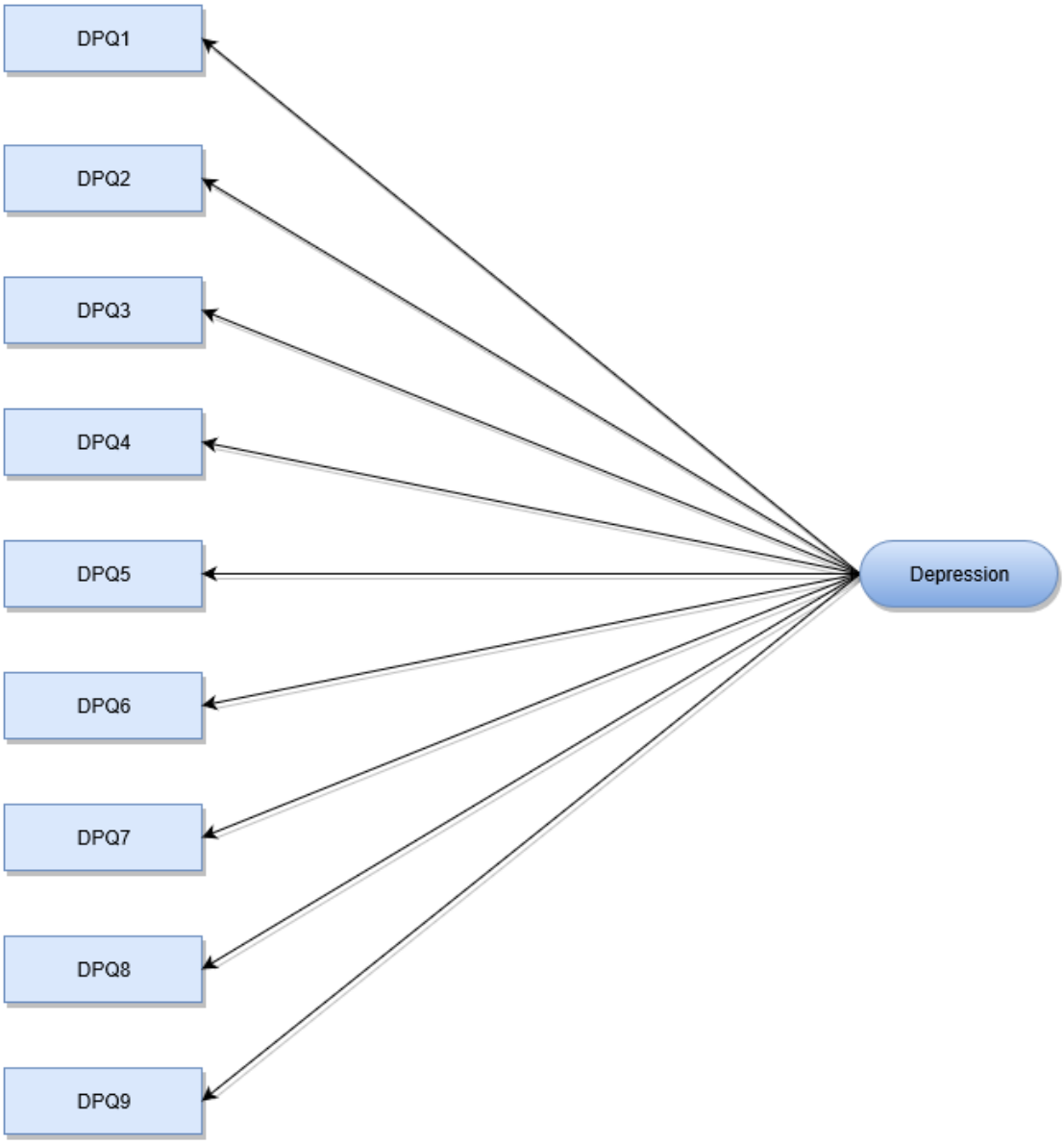

Figure 2. Measurement model depiction of the latent construct of Depression.

CHAPTER IV

RESULTS

This study is a non-experimental, secondary analysis using cross-sectional data from three cycles of the National Health and Nutrition Examination Survey (NHANES), from 2005 to 2010, to examine theoretical pathways linking measured variables and latent constructs. After the data were downloaded and merged, the sample consisted of 31,034 participants; however, after removing participants under the age of 20, the sample size was 17,132 participants. This sample size is sufficient to complete the final SEM analyses. When cases with missing data were removed, 10,574 participants remained. Therefore, the sample size with complete cases is also sufficient and was used to complete the analyses. The dataset with complete cases was used to study the differences between ML and QML under 3 conditions of data complexity: 1) simple random sample conditions, 2) with complex survey design, and 3) and with a modification to the dataset to mimic the missingness of the raw NHANES dataset to incorporate multiple imputation. The last component of the study was to apply QML with the Satorra-Bentler correction to the full NHANES dataset.

Table 1.

Demographics from NHANES Complete Case (CC) analysis (n=10,574), unweighted NHANES raw data (n=17,132), and with 6 year weighting (N=153,038,278) for participants over 20 years of age.

	NHANES Weighted		NHANES unweighted		Complete Cases Sample		% Completing Survey
	No.	Percent	No.	Percent	No.	Percent	
Ethnicity							
Mexican American	18,000,000	8.38%	3176	18.54%	1526	14.43%	48.05%
Other Hispanic	9,500,000	4.42%	1452	8.48%	761	7.20%	52.41%
Non-Hispanic White	150,000,000	69.85%	8232	48.05%	5929	56.07%	72.02%
Non-Hispanic Black	24,000,000	11.18%	3472	20.27%	1929	18.24%	55.56%
Other, Including Multi-Racial	13,000,000	6.05%	800	4.67%	429	4.06%	53.63%
Age Group							
20-29	41000000	19.09%	3006	17.55%	1581	14.95%	52.59%
30-39	40000000	18.63%	2910	16.99%	1660	15.70%	57.04%
40-49	44000000	20.49%	2899	16.92%	1766	16.70%	60.92%
50-59	39000000	18.16%	2520	14.71%	1619	15.31%	64.25%
60-69	25000000	11.64%	2648	15.46%	1817	17.18%	68.62%
70-79	16000000	7.45%	1891	11.04%	1337	12.64%	70.70%
80+	9500000	4.42%	1258	7.34%	794	7.51%	63.12%
Food Security (FS) (RAW: N=12797; with weighting N=175,724,587)							
HIGH FS	170,000,000	96.74%	12558	98.13%	10392	98.28%	82.75%
MARGINAL FS	120,000	0.07%	10	0.08%	8	0.08%	80.00%
LOW FS	900,000	0.51%	108	0.84%	79	0.75%	73.15%
VERY LOW FS	1,100,000	0.63%	121	0.95%	95	0.90%	78.51%

4.1 Demographics

The NHANES dataset was comprised of 8303 males (48.45%) and 8829 females (51.52%) that with weighting represent 48.17% and 51.83% of the population respectively. The complete case sample's gender ratio differed slightly with 5291 (50.04%) and 5283 (49.96) for males and females respectively. The mean and median age in the sample was 49.64 and 49 respectively with a maximum value of 85. When sampling weights were added, the mean age was 46.785 (SE=0.3259). Further demographics are described in Table 1 as well as the percentage of groups completing the NHANES survey.

4.2 Variable Characteristics

Each variable was chosen for its unique characteristics to be included in the model. The skewness and kurtosis of age, DPQ030 and DPQ040 are within accepted values for ML; however, cotinine, DPQ010, DPQ020, DPQ050, DPQ060, DPQ070, DPQ080, DPQ090, and food security all show varying degrees of kurtosis outside of the normally accepted values. Cotinine has a very wide continuous range, while the DPQ measures that make up the Depression construct range from 0 to 3 were treated as continuous. Table 2 provides means, ranges, and normality values for each variable included in the analyses. Histograms, shown in Figure 3 and 4, illustrate the skewness in both the unweighted and survey weighted variables. Age shows the most change in distribution and is the most normally distributed variable used in the analyses.

4.3 Confirmatory Factor Analysis of the Depression Construct

Confirmatory factor analysis of the DPQ screener showed moderate to high factor loadings for all items comprising the construct of Depression as shown in Figure 5.

Table 2.

Descriptive Statistics of variables from the NHANES Sample.

	Mean	*SD*	Min	Max	Skew	Kurtosis
Cotinine	59.78	129.2	0.01	1438	2.6	8.11
Age	49.64	18.31	20	85	0.14	-1.12
DPQ010	0.34	0.71	0	3	2.27	4.71
DPQ020	0.36	0.72	0	3	2.24	4.58
DPQ030	0.63	0.95	0	3	1.41	0.84
DPQ040	0.74	0.93	0	3	1.18	0.46
DPQ050	0.37	0.76	0	3	2.24	4.3
DPQ060	0.25	0.63	0	3	2.88	8.2
DPQ070	0.25	0.64	0	3	2.88	8.13
DPQ080	0.16	0.52	0	3	3.73	14.61
DPQ090	0.06	0.31	0	3	6.81	52.02
Food Security	0.24	1.45	0	10	5.94	33.85

Composite reliability was 0.834, showing a high reliability among these items for this population. Coefficients and standard errors of the Depression structure are shown in Table 5.

4.4 Missing data

Each variable was assessed for missing data from the NHANES dataset. The amount of missing data ranged from 0% to 25.3% as shown for each variable in Appendix D and the top portion of Figure 8. Missingness was analyzed in two ways. First, components of NHANES data were compared to the demographic makeup of the sample to determine if race, age group, or food security status had an effect of completion

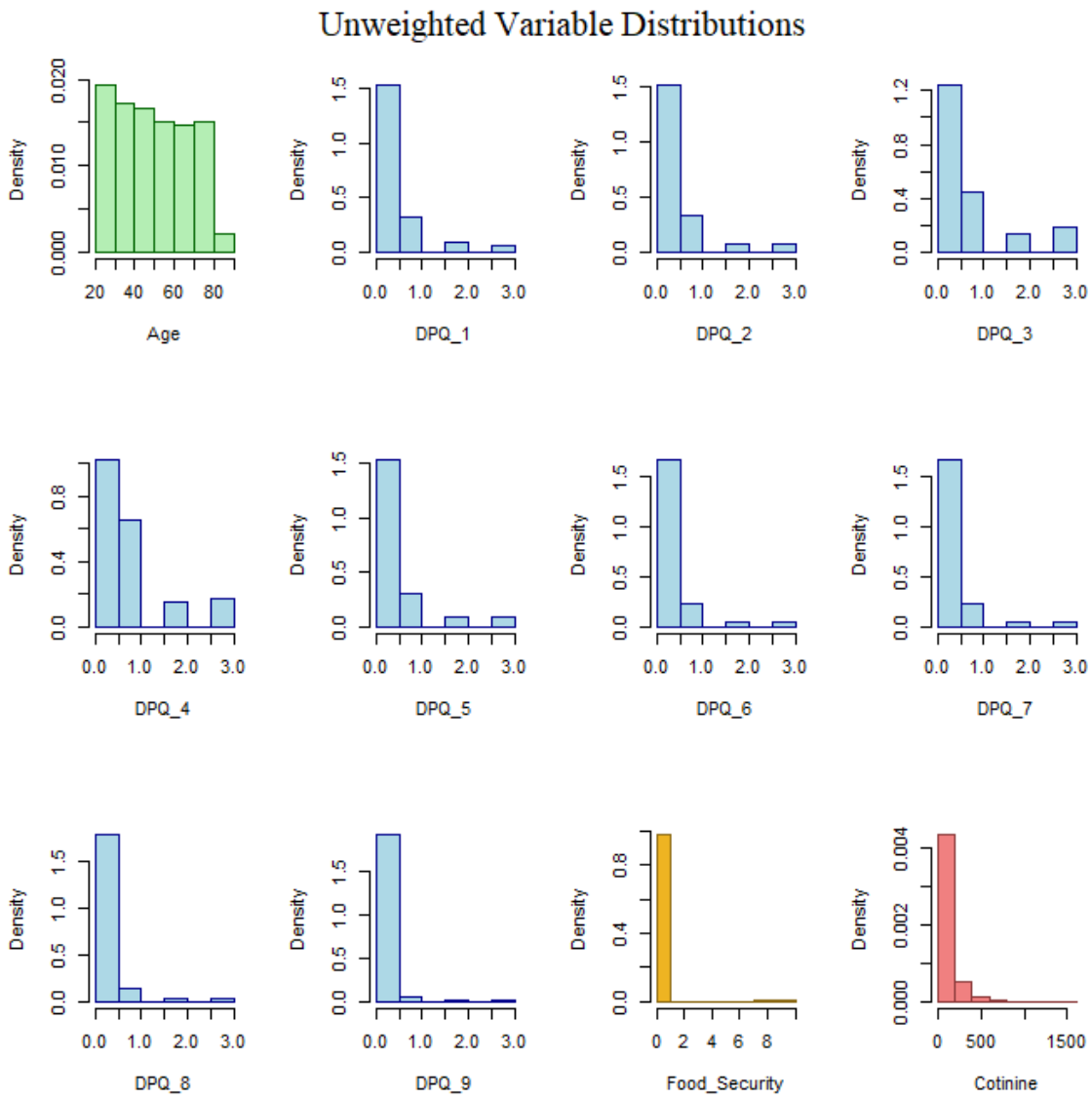

Figure 3. Histograms showing skewness of each of the unweighted variables used from NHANES data cycles 2005-2010.

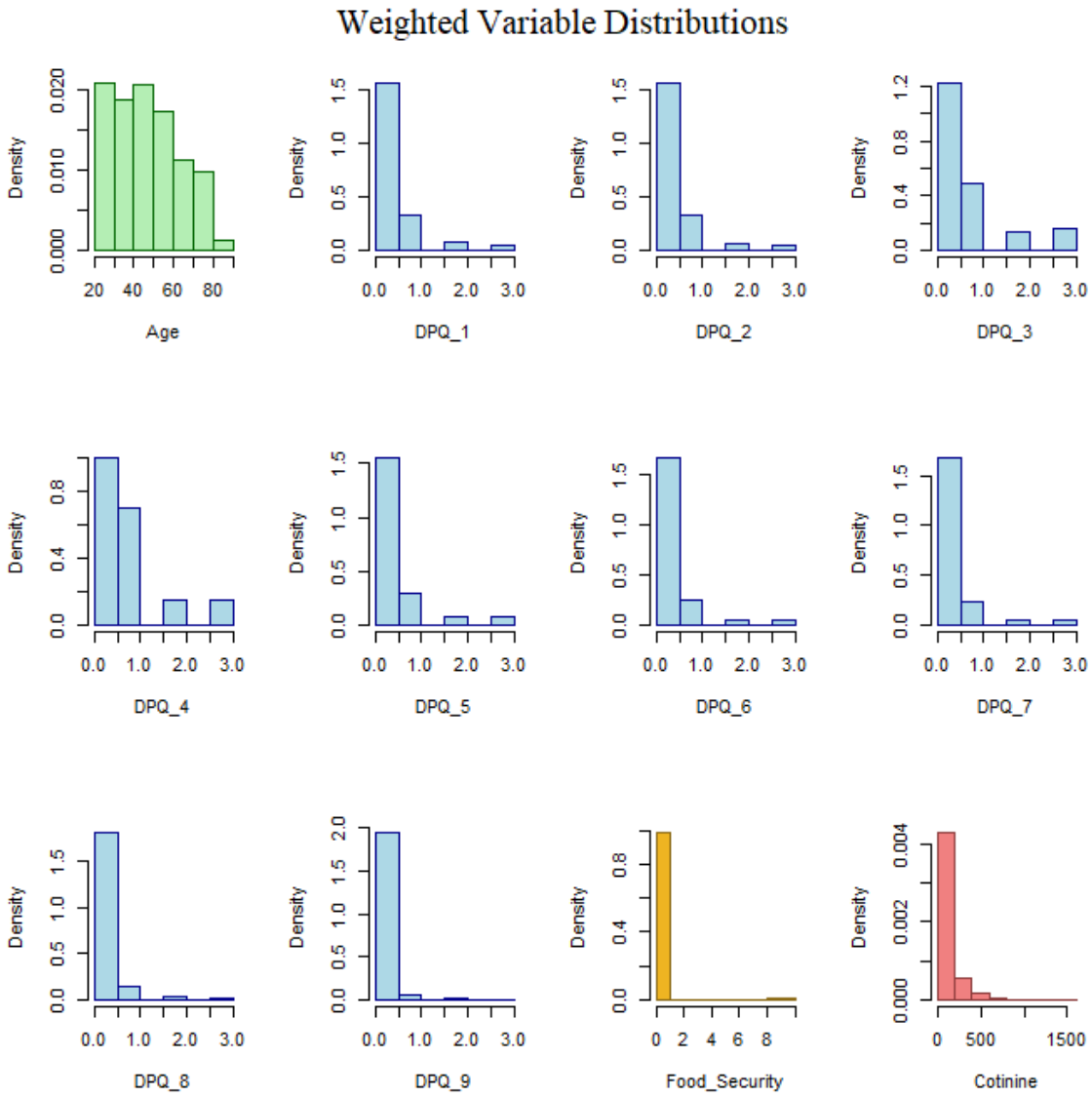

Figure 4. Histograms showing skewness of each of the weighted variables used from NHANES data cycles 2005-2010.

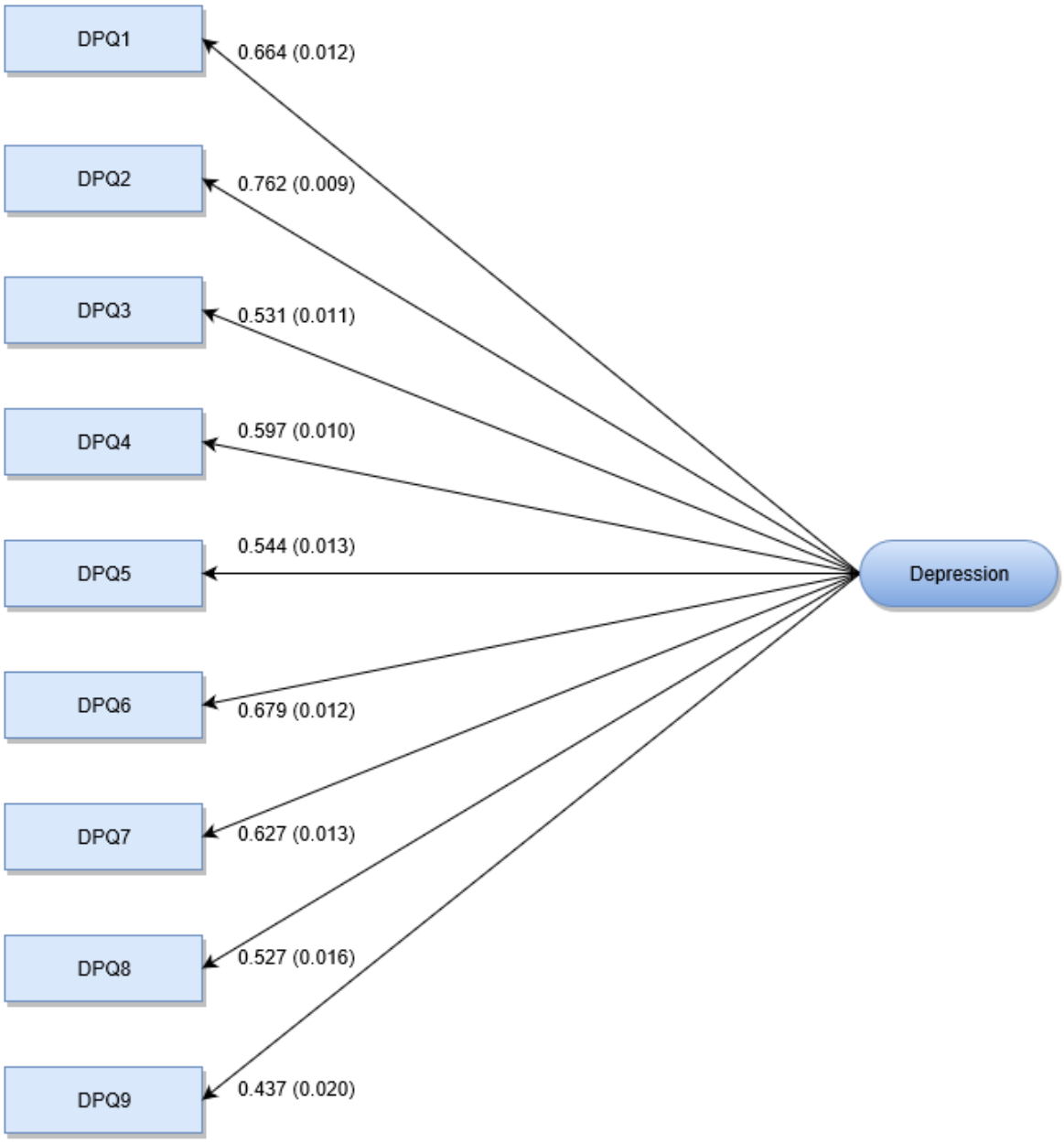

Figure 5. Confirmatory factor analysis model for items measuring the latent construct of Depression. Standardized factor loadings and standard errors are provided.

of the measures shown in Table 3. Secondly, NHANES components were assessed for patterns of incompleteness among participants as shown in the lower portion of Figure 8.

A pattern of missing data was present in the full NHANES data due to race (Figure 6)' affirming that it was missing at random (MAR); however, there did not seem to be any distinguishable patterned combinations of missingness among the variables in the model (Figure 8).

The deletion of observations from the complete case dataset in order to test the later iterations of the SEM model using multiple imputations, incorporated the patterns of missingness by race identified in the original NHANES dataset. The patterns of missingness replicated in modified complete case data are shown in Figures 7 and 9. Due to the lower completion rate of all components by Mexican-American and other Hispanics, FSSM missingness appeared to be condensed to Black and Multi-racial participants that had higher rates of completion of the NHANES survey components (Table 3). Pattern combinations of missingness among variables match the Full NHANES data well.

Multiple imputations were then created using the mice package (van Buuren, & Groothuis-Oudshoorn, 2011). Five imputations were created for use with the last pair of SEM models. Each imputation was processed with five iterations, which (Liu & Brown, 2013) have been shown to be sufficient. The *mice* package uses an iterative algorhythm that is computationally more precise so that fewer iterations are required for reasonable convergence compared to other Gibbs sampler programs (van Buuren & Groothuis-Oudshoorn, 2011). Convergence graphs for the imputed variables are shown in Figure 10.

Table 3.

Component Missingness from NHANES Raw Data (N=17,132) by Race, Age Group, and FS Status.

	Participant Demographics		**DPQ Missingness**		**FSSM Missingness**		**Cotinine Missingness**	
Ethnicity	No.	Percent	No.	Percent	No.	Percent	No.	Percent
Mexican American	3176	18.54	445	19.01	1336	30.82	275	17.19
Other Hispanic	1452	8.48	202	8.62	534	12.32	127	7.94
Non-Hispanic White	8232	48.05	964	41.18	1287	29.69	637	39.81
Non-Hispanic Black	3472	20.27	533	22.77	980	22.61	487	29.88
Other, including Multi-Racial	800	4.67	197	8.42	198	4.57	83	5.19
Age Group								
20-29	3006	17.55	403	17.21	1040	23.99	316	19.75
30-39	2910	16.99	452	19.30	880	20.30	284	17.75
40-49	2899	16.92	363	15.51	810	18.69	209	13.06
50-59	2520	14.71	275	11.75	636	14.67	199	12.44
60-69	2648	15.46	275	11.75	563	12.99	214	13.38
70-79	1891	11.04	250	10.68	286	6.60	171	10.69
80+	1258	7.34	323	13.80	120	2.77	207	12.94
FS Status								
High FS	12558	98.13	1662	97.59			1182	97.93
Marginal FS	10	0.08	2	.12			0	0
Low FS	108	0.84	23	1.35			9	0.75
Very Low FS	121	0.95	16	.94			16	1.33

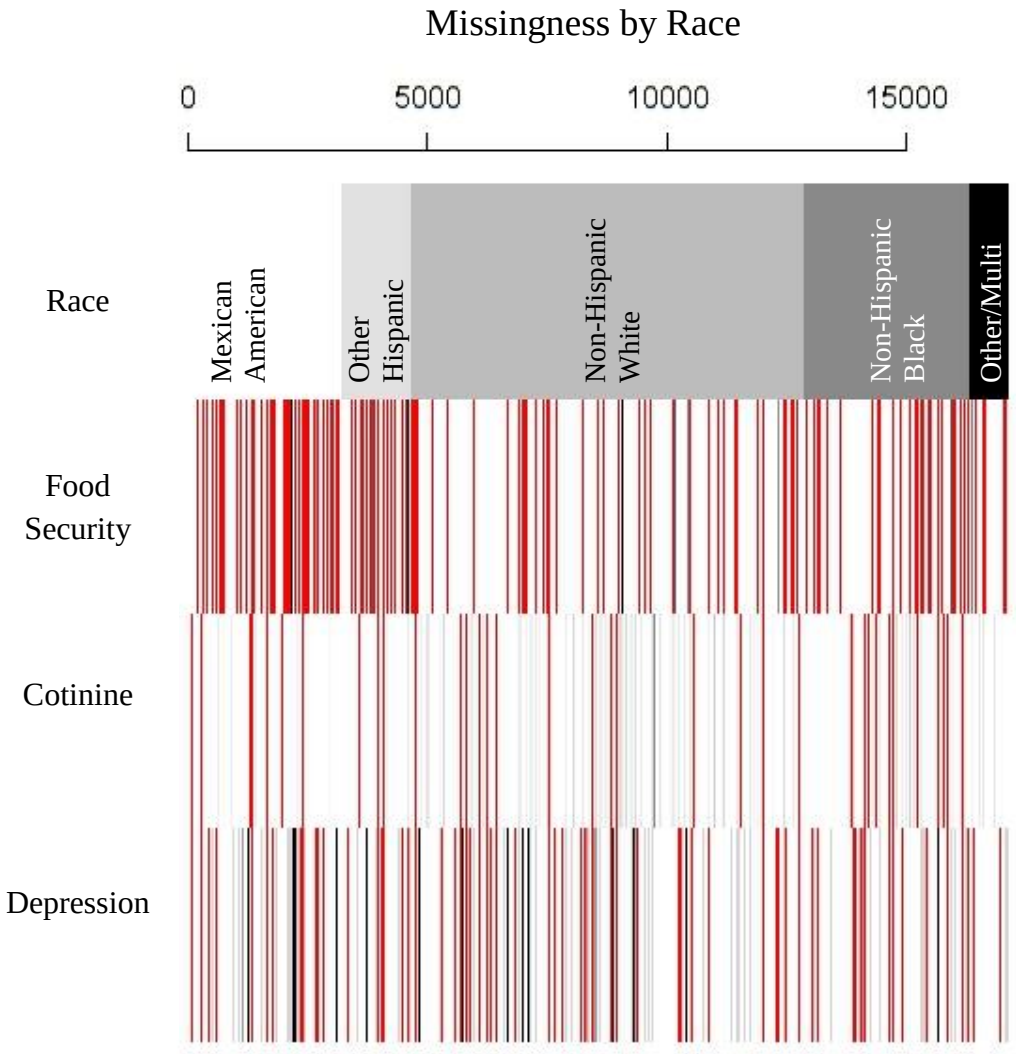

Figure 6. Patterns of missing data by race from the full NHANES data. Mexican-Americans and other Hispanics were far less likely to complete the food security survey module.

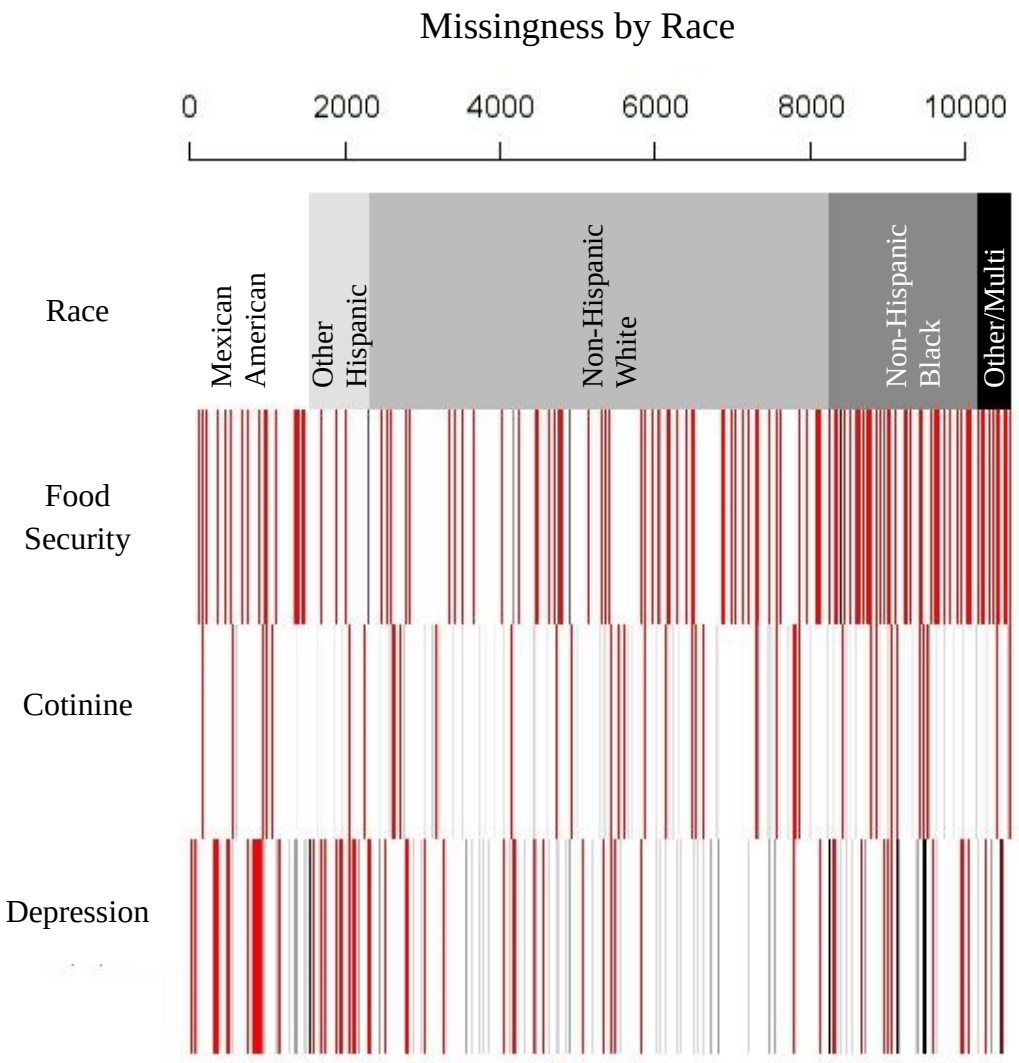

Figure 7. Patterns of missing data by race in the modified complete case dataset to replicate missingness from the full NHANES data.

Figure 8. Proportion of missing data from the full NHANES dataset with percentage (Top) and patterns (Bottom) of component missingness among NHANES participants.

Figure 9. Proportion of missing data in the modified complete case dataset with replicated missingness from the full NHANES dataset with percentage (Top) and patterns (Bottom) of component missingness among NHANES participants.

Imputation Iterations

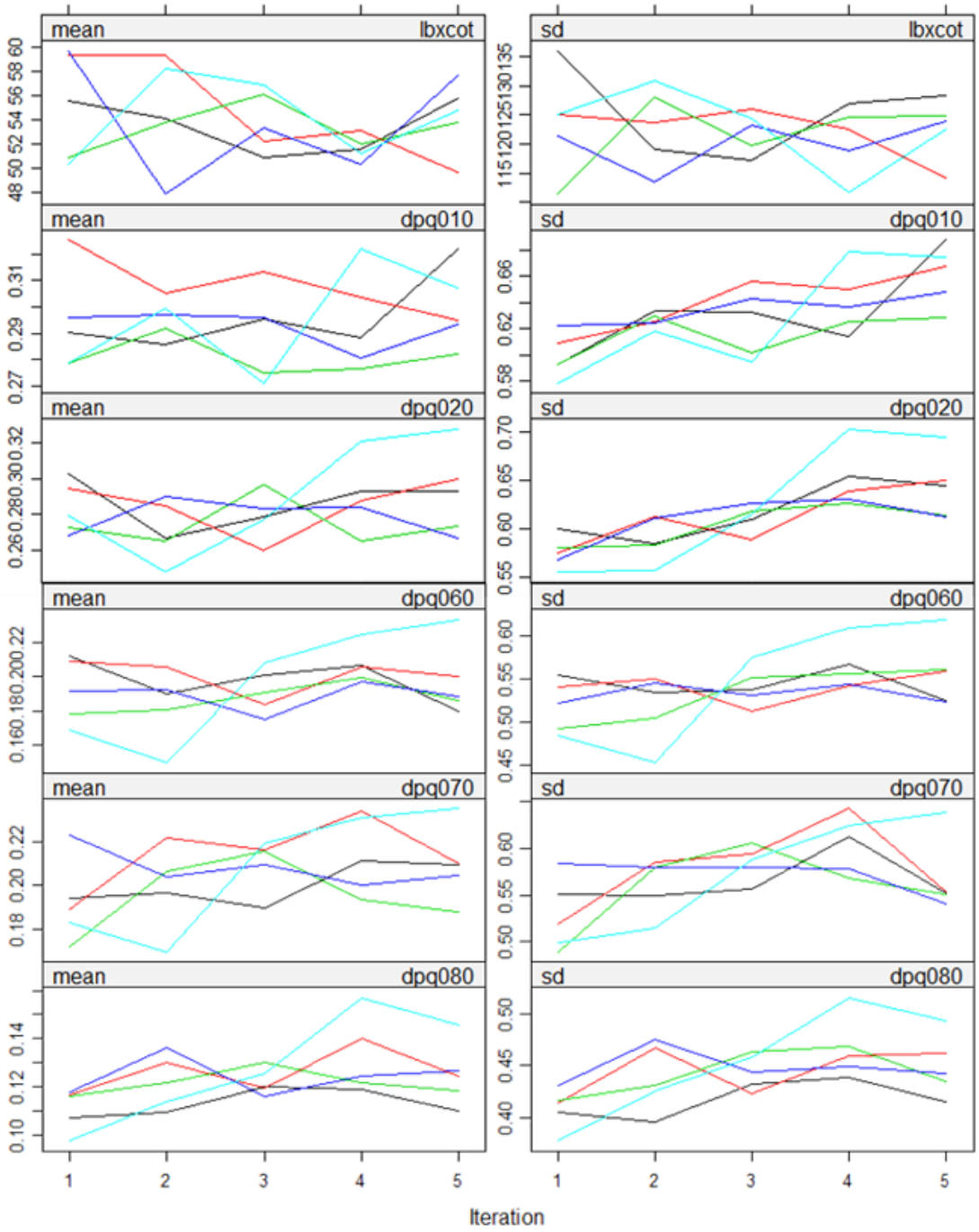

Figure 10. Iterations of imputations showing reasonable convergence from five imputations and five iterations.

Imputation Iterations

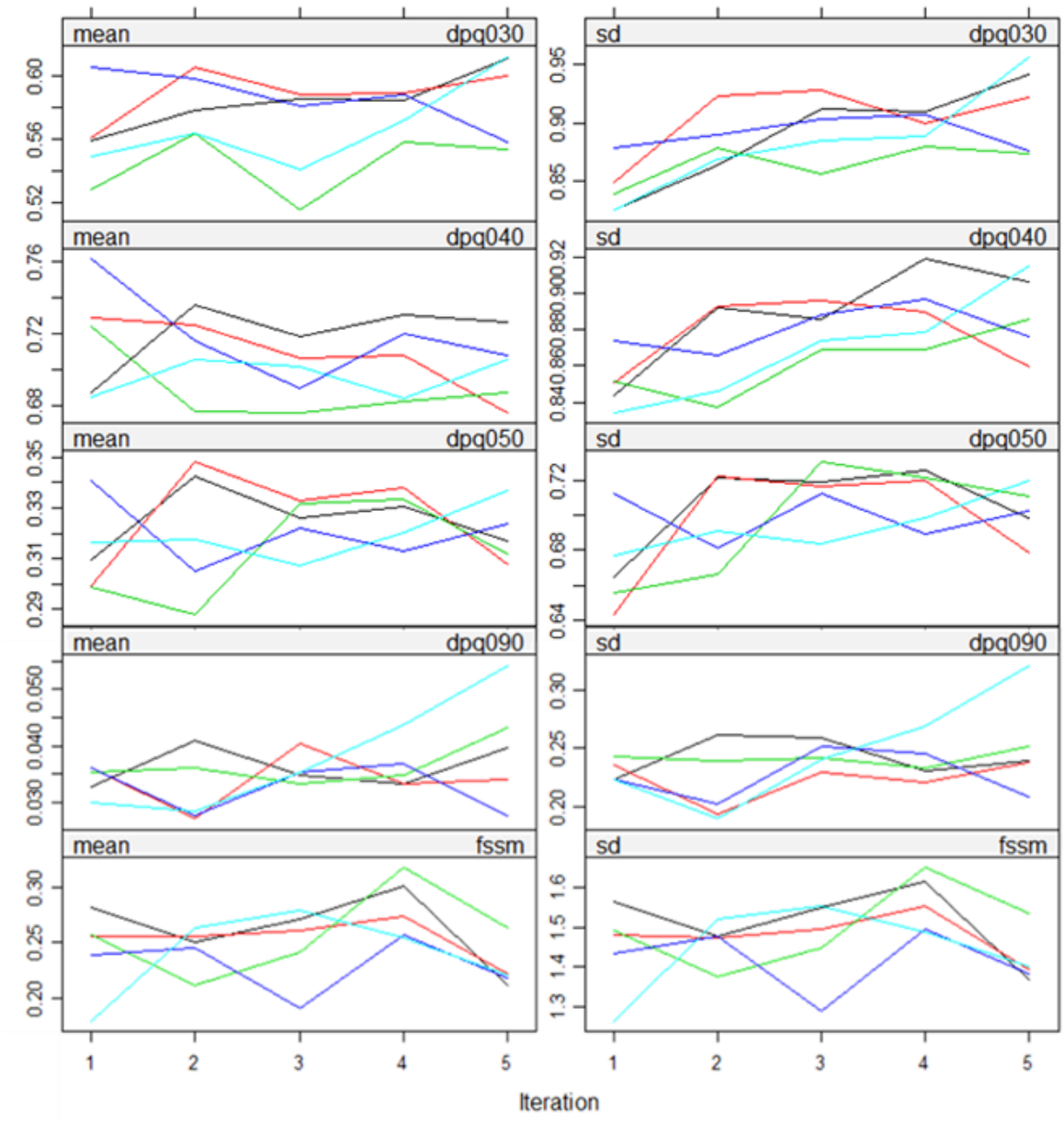

Figure 10 continued.

4.5 Model Fit Indices.

Comparisons of model fit indices between the maximum liklihood estimator and quasi-maximum likelihood with Satorra-Bentler correction had similar differences among each pair of models tested. The difference in the number of free parameters (11) resulted in the similarities in Akaikes Information Criterion and Bayesian Information Criterion with and without sample size adjustments between each pair of ML and QML models. These values show that the models using ML were lower between pairs and also increase with complexity of the datasets. The Chi square tests were significant for all models tested regardless of estimator used; however, because this test is sensitive to the large sample size, other indices of fit were examined. A comparison of all model fit tests and indices is shown in Table 4.

The root mean square error of approximation was 0.01 point lower in the QML model than in the ML when using complete cases analysis. In the subsequent models, after adding the survey design and then the imputations, the RMSEA was 0.02 points lower in the QML estimated models. Following the order of data complexity and decreasing RMSEA, the 90% confidence interval increased width in all QML estimations versus their ML counterpart by values of 0.002, 0.003, and 0.004, but the increase in spread decreased the lower bound value, while the upper bound value was unchanged.

The Standardized Root Mean Square Residual followed the same pattern as the RMSEA between model pairs. The SRMR was 0.03 points lower in the base QML model versus the ML model. The SRMR was lower in the subsequent pairs of models, with the difference being 0.02 lower when adding the survey design, and 0.03 lower when adding the imputations.

Table 4.

Fit indices for each SEM model

	ML	QML	SURVEY ML	SURVEY QML	SURVEY ML MI	SURVEY QML MI
Iterations	73.000	107.000	73.000	95.000	76.000	90.000
Degrees Of Freedom	51.000	51.000	51.000	51.000	51.000	51.000
Satorra-Bentler Correction Factor		2.217		2.998		3.305
Chi-Square Test P Value:	<0.001	<0.001	<0.001	<0.001	<0.001	<0.001
Loglikelihood (H0)	-203078.963	-203078.963	-194237.145	-194237.145	-194646.212	-194646.212
Loglikelihood (H1)	-202026.408	-202026.408	-193051.350	-193051.350	-193518.650	-193518.650
Number Of Free Parameters	26.000	37.000	26.000	37.000	26.000	37.000
Akaike Information Criteria (AIC)	406209.927	406231.927	388526.290	388548.290	389344.425	389366.425
Bayesian Information Criteria(BIC)	406398.846	406500.774	388715.210	388817.138	389533.345	389635.272
Sample-Size Adjusted Bayesian (BIC)	406316.222	406383.193	388632.585	388699.557	389450.720	389517.691
RMSEA	0.062	0.061*	0.066	0.064*	0.064	0.062*
90% Confidence Interval	.0590-0.064	.0570-0.064	.063-.068	.060-.068	0.062-.0660	0.058-.0660
SRMR	.035	.032	.037	.035	.037	.034
Comparative Fit Index (CFI)	0.925	0.927*	0.914	0.916*	0.917	0.920*
Tucker-Lewis Index (TLI)	0.903	0.906*	0.888	0.892*	0.892	0.896*

* Denotes robust statistic for QML with Satorra-Bentler correction as produced by Lavaan package in R.

The Comparative Fit Index (CFI) and Tucker-Lewis Index (TLI) were both higher in the QML models. The differences in models under QML and ML estimators using complete case analysis were 0.002 and 0.003 for the CFI and TLI respectively. With the addition of the survey design, the differences were the same for the CFI, but increased to 0.004 for the TLI. Finally, for the last pair of models, after adding in the imputations, the differences in values were 0.003 and 0.004 for the CFI and TLI respectively.

4.6 Estimations of Coefficients and Standard Errors.

Between models using maximum likelihood and quasi-maximum likelihood with Satorra-Bentler esimations at each level of data complexity, the coefficients were identical as presented in Table 5. QML with Satorra-Bentler correction accounts for the non-normality of the variables' distributions, by which it increases robustness and produces larger standard errors. The average percent increase in standard error of variables between ML and QML using the complete case dataset was nearly 95%. The average change in standard error between QML and ML increased to 154.26% when applying the complex survey design. However, when adding the multiple imputations into the design, the standard errors remained nearly the same as using the complete case analysis with the complex survey design. The average percent change between ML and QML estimation for this pair was 152.42%. The coefficients remained relatively the same- varying only about 10 percent from the complete case analysis models.

4.7 Modification Indices.

The Satorra-Bentler correction is used to scale the calculated Lagrange Multiplier value produced under the QML estimator to match the true distribution (Oberski, 2014).

Table 5.

Comparison of SEM coefficients and standard errors between ML and QML.

Complete Cases without survey design.				
	Coefficient	Standard Error		Percent change
		ML	QML	in absolute values
Measurement Model (Standardized):				
Depression on				
DPQ010	0.662	0.006	0.012	100.00%
DPQ020	0.762	0.005	0.009	80.00%
DPQ030	0.531	0.008	0.01	25.00%
DPQ040	0.595	0.007	0.009	28.57%
DPQ050	0.546	0.008	0.012	50.00%
DPQ060	0.681	0.006	0.012	100.00%
DPQ070	0.626	0.007	0.013	85.71%
DPQ080	0.528	0.008	0.016	100.00%
DPQ090	0.439	0.009	0.02	122.22%
Structural Model (Unstandardized):				
FS on Age	-0.006	0.001	0.001	0.00%
Cotinine on Age	-0.475	0.065	0.056	13.85%
Cotinine on FS	8.561	0.861	1.219	41.58%
Depression on age	-0.003	0.001	0.001	0.00%
Cotinine on Depression	10.264	1.279	1.392	8.84%
Depression on FS	0.155	0.008	0.014	75.00%
Variances (Unstandardized):				
DPQ010	0.24	0.004	0.009	125.00%
DPQ020	0.173	0.003	0.006	100.00%
DPQ030	0.594	0.009	0.013	44.44%
DPQ040	0.515	0.008	0.011	37.50%
DPQ050	0.344	0.005	0.01	100.00%
DPQ060	0.172	0.003	0.006	100.00%
DPQ070	0.206	0.003	0.007	133.33%
DPQ080	0.146	0.002	0.006	200.00%
DPQ090	0.058	0.001	0.004	300.00%
FS	1.964	0.027	0.118	337.04%
Cotinine	14549.97	200.374	522.772	160.90%
Average change:				94.96%

Table 5 continued.

Comparison of SEM models with survey design between QML and ML.

Complete Cases with Complex Survey Design.							
	Coefficient	Standard Error (SE)		Coeff % change from Base ML	SE % change from Base ML	SE % change from Base ML	% Change between current pair
		ML	QML		ML	QML	
Measurement Model (Standardized):					Percent change		
Depression on							
DPQ010	0.669	0.006	0.015	1.06%	0.00%	150.00%	150.00%
DPQ020	0.76	0.005	0.011	0.26%	0.00%	120.00%	120.00%
DPQ030	0.513	0.008	0.013	3.39%	0.00%	62.50%	62.50%
DPQ040	0.586	0.007	0.011	1.51%	0.00%	57.14%	57.14%
DPQ050	0.554	0.008	0.015	1.47%	0.00%	87.50%	87.50%
DPQ060	0.677	0.006	0.014	0.59%	0.00%	133.33%	133.33%
DPQ070	0.617	0.007	0.013	1.44%	0.00%	85.71%	85.71%
DPQ080	0.496	0.008	0.022	6.06%	0.00%	175.00%	175.00%
DPQ090	0.433	0.009	0.022	1.37%	0.00%	144.44%	144.44%
Structural Model (Unstandardized):							
FS on Age	-0.004	0.001	0.001	33.33%	0.00%	0.00%	0.00%
Cotinine on Age	-0.54	0.072	0.086	13.68%	-10.77%	32.31%	19.44%
Cotinine on FS	10.807	1.086	2.035	26.24%	-26.13%	136.35%	87.38%
Depression on age	-0.003	0.001	0.001	0.00%	0.00%	0.00%	0.00%
Cotinine on Depression	9.719	1.304	1.526	5.31%	-1.95%	19.31%	17.02%
Depression on FS	0.18	0.01	0.018	16.13%	-25.00%	125.00%	80.00%
Variances (Unstandardized):							
DPQ010	0.199	0.003	0.01	17.08%	25.00%	150.00%	233.33%
DPQ020	0.15	0.003	0.008	13.29%	0.00%	166.67%	166.67%
DPQ030	0.572	0.008	0.019	3.70%	11.11%	111.11%	137.50%
DPQ040	0.481	0.007	0.017	6.60%	12.50%	112.50%	142.86%
DPQ050	0.311	0.005	0.013	9.59%	0.00%	160.00%	160.00%
DPQ060	0.155	0.003	0.007	9.88%	0.00%	133.33%	133.33%
DPQ070	0.194	0.003	0.009	5.83%	0.00%	200.00%	200.00%
DPQ080	0.128	0.002	0.007	12.33%	0.00%	250.00%	250.00%
DPQ090	0.045	0.001	0.005	22.41%	0.00%	400.00%	400.00%
FS	1.27	0.017	0.134	35.34%	37.04%	396.30%	688.24%
Cotinine	15069.19	207.491	786.847	3.57%	-3.55%	292.69%	279.22%
Average change:				9.67%	0.70%	142.35%	154.26%

Table 5 Continued.

Comparison of SEM coefficients and standard errors between ML and QML.

Imputed Complete Cases with Complex Survey Design.							
	Coefficient	Standard Error (SE)		Coeff % change from Base ML	SE % change from Base ML	SE % change from Base ML	% Change between current pair
		ML	QML		ML	QML	
Measurement Model (Standardized):					Percent change		
Depression on							
DPQ010	0.66	0.007	0.015	0.30%	16.67%	150.00%	114.29%
DPQ020	0.759	0.005	0.011	0.39%	0.00%	120.00%	120.00%
DPQ030	0.513	0.008	0.013	3.39%	0.00%	62.50%	62.50%
DPQ040	0.582	0.007	0.012	2.18%	0.00%	71.43%	71.43%
DPQ050	0.557	0.008	0.016	2.01%	0.00%	100.00%	100.00%
DPQ060	0.676	0.006	0.013	0.73%	0.00%	116.67%	116.67%
DPQ070	0.62	0.007	0.014	0.96%	0.00%	100.00%	100.00%
DPQ080	0.495	0.008	0.023	6.25%	0.00%	187.50%	187.50%
DPQ090	0.425	0.009	0.022	3.19%	0.00%	144.44%	144.44%
Structural Model (Unstandardized):							
FS on Age	-0.004	0.001	0.001	33.33%	0.00%	0.00%	0.00%
Cotinine on Age	-0.569	0.072	0.085	19.79%	10.77%	30.77%	18.06%
Cotinine on FS	10.63	1.091	1.828	24.17%	26.71%	112.31%	67.55%
Depression on age	-0.002	0.001	0.001	33.33%	0.00%	0.00%	0.00%
Cotinine on Depression	9.668	1.311	1.696	5.81%	2.50%	32.60%	29.37%
Depression on FS	0.176	0.01	0.018	13.55%	25.00%	125.00%	80.00%
Variances (Unstandardized):							
DPQ010	0.204	0.003	0.009	15.00%	25.00%	125.00%	200.00%
DPQ020	0.152	0.003	0.008	12.14%	0.00%	166.67%	166.67%
DPQ030	0.575	0.008	0.018	3.20%	11.11%	100.00%	125.00%
DPQ040	0.487	0.007	0.017	5.44%	12.50%	112.50%	142.86%
DPQ050	0.31	0.005	0.013	9.88%	0.00%	160.00%	160.00%
DPQ060	0.154	0.003	0.008	10.47%	0.00%	166.67%	166.67%
DPQ070	0.194	0.003	0.009	5.83%	0.00%	200.00%	200.00%
DPQ080	0.129	0.002	0.007	11.64%	0.00%	250.00%	250.00%
DPQ090	0.046	0.001	0.005	20.69%	0.00%	400.00%	400.00%
FS	1.268	0.017	0.132	35.44%	37.04%	388.89%	676.47%
Cotinine	15232.56	209.738	762.383	4.69%	4.67%	280.48%	263.49%
Average change:				10.92%	6.61%	142.44%	152.42%

The Lagrange multiplier values that appear in Tables 5, 6, and 7 under the QML estimator heading are the scaled values using the Satorra-Bentler correction. The Satorra-Bentler correction had a corrective value of 2.217 in the first model under quasi-maximum likelihood (Table 4). The Satorra-Bentler correction values were 2.998 and 3.305 for the analysis of the complete case data set using the complex survey design and also for the analysis using the survey design and incorporating multiple imputations respectively.

The Lagrange Multiplier values in the modification indices from each subsequent model diverged greatly from the complete case analysis using ML; however, there was less difference between ML and QML when using the same level of data complexity (Tables 6, 7, & 8). Between ML and QML for the complete case analysis (without the survey design), the average difference (using absolute value change) was only 0.09%, which came mostly from the Lagrange multiplier (LM) value given for adding Cotinine to the measurement model of Depression and differing by 4.92%, as shown in Table 6. The only other differing LM value given between this pair of SEM models was to allow DPQ040 to covary with DPQ080 within the Depression measurement model.

When adding the complex survey design to the ML and QML estimations, the divergence from the original ML modification index was 234.37% and 234.32%, respectively. The complex survey design vastly changed the LM values given for each proposed covariance, some changing as much as several thousand percent as shown in Table 7. The difference between the current ML and QML estimations among the dataset using complex survey design was again only between two variables, with the major difference coming from the LM value of regressing Age on Cotinine. The LM value for

Table 6.

Comparison of modification indices showing Lagrange Multiplier values for complete case dataset using ML and QML.

			ML	QML	% Change
			Value	Value	
Measurement model regressions					
Dep	by	Cotinine	73.314	77.108	-4.92%
Structural Regressions					
Dep	on	Cotinine	64.563	64.563	0.00%
Age	on	FS	0	0	0.00%
Age	on	Cotinine	0	0	0.00%
Age	on	Dep	0	0	0.00%
Covariances					
DPQ010	with	DPQ020	256.728	256.728	0.00%
DPQ010	with	DPQ030	12.776	12.776	0.00%
DPQ010	with	DPQ040	14.257	14.257	0.00%
DPQ010	with	DPQ050	0.374	0.374	0.00%
DPQ010	with	DPQ060	34.021	34.021	0.00%
DPQ010	with	DPQ070	30.872	30.872	0.00%
DPQ010	with	DPQ080	26.794	26.794	0.00%
DPQ010	with	DPQ090	26.046	26.046	0.00%
DPQ010	with	FS	7.469	7.469	0.00%
DPQ010	with	Cotinine	1.314	1.314	0.00%
DPQ020	with	DPQ030	102.669	102.669	0.00%
DPQ020	with	DPQ040	89.433	89.433	0.00%
DPQ020	with	DPQ050	107.543	107.543	0.00%
DPQ020	with	DPQ060	217.789	217.789	0.00%
DPQ020	with	DPQ070	18.809	18.809	0.00%
DPQ020	with	DPQ080	61.674	61.674	0.00%
DPQ020	with	DPQ090	34.128	34.128	0.00%
DPQ020	with	FS	0.072	0.072	0.00%
DPQ020	with	Cotinine	3.234	3.234	0.00%
DPQ030	with	DPQ040	651.769	651.769	0.00%
DPQ030	with	DPQ050	110.464	110.464	0.00%
DPQ030	with	DPQ060	58.908	58.908	0.00%
DPQ030	with	DPQ070	1.59	1.59	0.00%
DPQ030	with	DPQ080	2.817	2.817	0.00%
DPQ030	with	DPQ090	37.976	37.976	0.00%
DPQ030	with	FS	0.016	0.016	0.00%
DPQ030	with	Cotinine	5.92	5.92	0.00%

Table 6 continued.

			ML	QML	% Change
Covariances continued					
DPQ040	with	DPQ050	229.198	229.198	0.00%
DPQ040	with	DPQ060	179.062	179.062	0.00%
DPQ040	with	DPQ070	0.483	0.483	0.00%
DPQ040	with	DPQ080	0.888	0.887	-0.11%
DPQ040	with	DPQ090	131.045	131.045	0.00%
DPQ040	with	FS	21.102	21.102	0.00%
DPQ040	with	Cotinine	4.194	4.194	0.00%
DPQ050	with	DPQ060	18.34	18.34	0.00%
DPQ050	with	DPQ070	0.202	0.202	0.00%
DPQ050	with	DPQ080	0.01	0.01	0.00%
DPQ050	with	DPQ090	45.299	45.299	0.00%
DPQ050	with	FS	5.012	5.012	0.00%
DPQ050	with	Cotinine	0.51	0.51	0.00%
DPQ060	with	DPQ070	9.517	9.517	0.00%
DPQ060	with	DPQ080	1.044	1.044	0.00%
DPQ060	with	DPQ090	96.655	96.655	0.00%
DPQ060	with	FS	5.302	5.302	0.00%
DPQ060	with	Cotinine	0.306	0.306	0.00%
DPQ070	with	DPQ080	185.949	185.949	0.00%
DPQ070	with	DPQ090	0.001	0.001	0.00%
DPQ070	with	FS	9.79	9.79	0.00%
DPQ070	with	Cotinine	0.869	0.869	0.00%
DPQ080	with	DPQ090	63.148	63.148	0.00%
DPQ080	with	FS	4.684	4.684	0.00%
DPQ080	with	Cotinine	8.823	8.823	0.00%
DPQ090	with	FS	49.501	49.501	0.00%
DPQ090	with	Cotinine	0.19	0.19	0.00%
Average change:					0.09%

Table 7.

Comparison of modification indices showing Lagrange Multiplier values for complete case dataset with complex survey design using ML and QML.

			ML with Survey Design	% Change from Base ML	QML with Survey Design	% Change from Base ML	% change between ML and QML with Survey design
			Value		Value		
Measurement model regressions							
Dep	by	Cotinine	61.944	18.36%	63.337	15.75%	2.20%
Structural Regressions							
Dep	on	Cotinine	55.735	15.84%	55.735	15.84%	0.00%
Age	on	FS	0	0.00%	0	0.00%	0.00%
Age	on	Cotinine	25.13	-100.00%	0.904	-100.00%	-2679.87%
Age	on	Dep	0	0.00%	0	0.00%	0.00%
Covariances							
DPQ010	with	DPQ020	208.349	23.22%	208.349	23.22%	0.00%
DPQ010	with	DPQ030	17.812	-28.27%	17.812	-28.27%	0.00%
DPQ010	with	DPQ040	18.702	-23.77%	18.702	-23.77%	0.00%
DPQ010	with	DPQ050	0.071	426.76%	0.071	426.76%	0.00%
DPQ010	with	DPQ060	17.27	96.99%	17.27	96.99%	0.00%
DPQ010	with	DPQ070	24.297	27.06%	24.297	27.06%	0.00%
DPQ010	with	DPQ080	53.899	-50.29%	53.899	-50.29%	0.00%
DPQ010	with	DPQ090	30.552	-14.75%	30.552	-14.75%	0.00%
DPQ010	with	FS	4.952	50.83%	4.952	50.83%	0.00%
DPQ010	with	Cotinine	4.067	-67.69%	4.067	-67.69%	0.00%
DPQ020	with	DPQ030	117.218	-12.41%	117.218	-12.41%	0.00%
DPQ020	with	DPQ040	124.638	-28.25%	124.638	-28.25%	0.00%
DPQ020	with	DPQ050	125.549	-14.34%	125.549	-14.34%	0.00%
DPQ020	with	DPQ060	323.915	-32.76%	323.915	-32.76%	0.00%
DPQ020	with	DPQ070	23.124	-18.66%	23.124	-18.66%	0.00%
DPQ020	with	DPQ080	65.769	-6.23%	65.769	-6.23%	0.00%
DPQ020	with	DPQ090	50.289	-32.14%	50.289	-32.14%	0.00%
DPQ020	with	FS	0.215	-66.51%	0.215	-66.51%	0.00%
DPQ020	with	Cotinine	2.924	10.60%	2.924	10.60%	0.00%
DPQ030	with	DPQ040	717.222	-9.13%	717.222	-9.13%	0.00%
DPQ030	with	DPQ050	111.243	-0.70%	111.243	-0.70%	0.00%
DPQ030	with	DPQ060	66.778	-11.79%	66.778	-11.79%	0.00%
DPQ030	with	DPQ070	2.062	-22.89%	2.062	-22.89%	0.00%
DPQ030	with	DPQ080	0.042	6607.14%	0.042	6607.14%	0.00%
DPQ030	with	DPQ090	36.238	4.80%	36.238	4.80%	0.00%
DPQ030	with	FS	0.316	-94.94%	0.316	-94.94%	0.00%

Table 7 continued.

			ML with Survey Design	% Change from Base ML	QML with Survey Design	% Change from Base ML	% change between ML and QML with Survey design
			Value		Value		
Covariances Continued							
DPQ030	with	Cotinine	3.327	77.94%	3.327	77.94%	0.00%
DPQ040	with	DPQ050	247.978	-7.57%	247.978	-7.57%	0.00%
DPQ040	with	DPQ060	202.65	-11.64%	202.65	-11.64%	0.00%
DPQ040	with	DPQ070	1.502	-67.84%	1.502	-67.84%	0.00%
DPQ040	with	DPQ080	0.453	96.03%	0.453	96.03%	0.00%
DPQ040	with	DPQ090	167.482	-21.76%	167.482	-21.76%	0.00%
DPQ040	with	FS	16.811	25.52%	16.811	25.52%	0.00%
DPQ040	with	Cotinine	3.304	26.94%	3.304	26.94%	0.00%
DPQ050	with	DPQ060	14.244	28.76%	14.244	28.76%	0.00%
DPQ050	with	DPQ070	0.28	-27.86%	0.28	-27.86%	0.00%
DPQ050	with	DPQ080	1.075	-99.07%	1.075	-99.07%	0.00%
DPQ050	with	DPQ090	64.909	-30.21%	64.909	-30.21%	0.00%
DPQ050	with	FS	3.961	26.53%	3.961	26.53%	0.00%
DPQ050	with	Cotinine	0	100.00%	0	100.00%	0.00%
DPQ060	with	DPQ070	0.213	4368.08%	0.213	4368.08%	0.00%
DPQ060	with	DPQ080	5.537	-81.15%	5.537	-81.15%	0.00%
DPQ060	with	DPQ090	61.323	57.62%	61.323	57.62%	0.00%
DPQ060	with	FS	1.616	228.09%	1.616	228.09%	0.00%
DPQ060	with	Cotinine	0.134	128.36%	0.134	128.36%	0.00%
DPQ070	with	DPQ080	219.371	-15.24%	219.371	-15.24%	0.00%
DPQ070	with	DPQ090	4.138	-99.98%	4.138	-99.98%	0.00%
DPQ070	with	FS	12.976	-24.55%	12.976	-24.55%	0.00%
DPQ070	with	Cotinine	1.568	-44.58%	1.568	-44.58%	0.00%
DPQ080	with	DPQ090	95.741	-34.04%	95.741	-34.04%	0.00%
DPQ080	with	FS	4.245	10.34%	4.245	10.34%	0.00%
DPQ080	with	Cotinine	18.455	-52.19%	18.455	-52.19%	0.00%
DPQ090	with	FS	71.946	-31.20%	71.946	-31.20%	0.00%
DPQ090	with	Cotinine	1.52	-87.50%	1.52	-87.50%	0.00%
Average change:				234.37		234.32%	-45.38%

Table 8.

Comparison of modification indices showing Lagrange Multiplier values for dataset with complex survey design and deleted observations with imputations using ML and QML.

			ML with Survey Design and Imputations	% Change from Base ML	QML with Survey Design and Imputations	% Change from Base ML	% change between ML and QML with current pair
			Value		Value		
Measurement model regressions							
Dep	by	Cotinine	60.211	21.76%	61.425	19.36%	1.98%
Structural Regressions							
Dep	on	Cotinine	54.495	18.48%	54.495	18.48%	0.00%
Age	on	FS	0	0.00%	0	0.00%	0.00%
Age	on	Cotinine	18.677	-100.00%	0.778	-100.00%	-2300.64%
Age	on	Dep	0	0.00%	0	0.00%	0.00%
Covariances							
DPQ010	with	DPQ020	176.099	45.79%	176.099	45.79%	0.00%
DPQ010	with	DPQ030	7.319	74.56%	7.319	74.56%	0.00%
DPQ010	with	DPQ040	27.858	-48.82%	27.858	-48.82%	0.00%
DPQ010	with	DPQ050	0.009	4055.56%	0.009	4055.56%	0.00%
DPQ010	with	DPQ060	26.949	26.24%	26.949	26.24%	0.00%
DPQ010	with	DPQ070	21.708	42.21%	21.708	42.21%	0.00%
DPQ010	with	DPQ080	54.118	-50.49%	54.118	-50.49%	0.00%
DPQ010	with	DPQ090	21.667	20.21%	21.667	20.21%	0.00%
DPQ010	with	FS	8.074	-7.49%	8.074	-7.49%	0.00%
DPQ010	with	Cotinine	4.584	-71.34%	4.584	-71.34%	0.00%
DPQ020	with	DPQ030	101.432	1.22%	101.432	1.22%	0.00%
DPQ020	with	DPQ040	108.128	-17.29%	108.128	-17.29%	0.00%
DPQ020	with	DPQ050	116.902	-8.01%	116.902	-8.01%	0.00%
DPQ020	with	DPQ060	323.355	-32.65%	323.355	-32.65%	0.00%
DPQ020	with	DPQ070	14.015	34.21%	14.015	34.21%	0.00%
DPQ020	with	DPQ080	56.653	8.86%	56.653	8.86%	0.00%
DPQ020	with	DPQ090	29.547	15.50%	29.547	15.50%	0.00%
DPQ020	with	FS	3.512	-97.95%	3.512	-97.95%	0.00%
DPQ020	with	Cotinine	1.105	192.67%	1.105	192.67%	0.00%
DPQ030	with	DPQ040	693.47	-6.01%	693.47	-6.01%	0.00%
DPQ030	with	DPQ050	101.724	8.59%	101.724	8.59%	0.00%
DPQ030	with	DPQ060	56.994	3.36%	56.994	3.36%	0.00%
DPQ030	with	DPQ070	9.716	-83.64%	9.716	-83.64%	0.00%
DPQ030	with	DPQ080	1.513	86.19%	1.513	86.19%	0.00%
DPQ030	with	DPQ090	40.132	-5.37%	40.132	-5.37%	0.00%
DPQ030	with	FS	0.476	-96.64%	0.476	-96.64%	0.00%

Table 8 Continued.

			ML with Survey Design and Imputations	% Change from Base ML	QML with Survey Design and Imputations	% Change from Base ML	% change between ML and QML with current pair
Covariances Continued							
DPQ030	with	Cotinine	4.852	22.01%	4.852	22.01%	0.00%
DPQ040	with	DPQ050	240.303	-4.62%	240.303	-4.62%	0.00%
DPQ040	with	DPQ060	224.864	-20.37%	224.865	-20.37%	0.00%
DPQ040	with	DPQ070	0.041	1078.05%	0.041	1078.05%	0.00%
DPQ040	with	DPQ080	1.36	-34.71%	1.36	-34.71%	0.00%
DPQ040	with	DPQ090	148.165	-11.55%	148.166	-11.56%	0.00%
DPQ040	with	FS	8.288	154.61%	8.288	154.61%	0.00%
DPQ040	with	Cotinine	3.315	26.52%	3.315	26.52%	0.00%
DPQ050	with	DPQ060	11.465	59.97%	11.465	59.97%	0.00%
DPQ050	with	DPQ070	1.397	-85.54%	1.397	-85.54%	0.00%
DPQ050	with	DPQ080	0.017	-41.18%	0.017	-41.18%	0.00%
DPQ050	with	DPQ090	42.736	6.00%	42.736	6.00%	0.00%
DPQ050	with	FS	6.769	-25.96%	6.769	-25.96%	0.00%
DPQ050	with	Cotinine	1.615	-68.42%	1.615	-68.42%	0.00%
DPQ060	with	DPQ070	2.478	284.06%	2.478	284.06%	0.00%
DPQ060	with	DPQ080	1.742	-40.07%	1.742	-40.07%	0.00%
DPQ060	with	DPQ090	43.516	122.11%	43.516	122.11%	0.00%
DPQ060	with	FS	1.744	204.01%	1.744	204.01%	0.00%
DPQ060	with	Cotinine	0.253	20.95%	0.253	20.95%	0.00%
DPQ070	with	DPQ080	210.651	-11.73%	210.651	-11.73%	0.00%
DPQ070	with	DPQ090	7.049	-99.99%	7.049	-99.99%	0.00%
DPQ070	with	FS	12.366	-20.83%	12.366	-20.83%	0.00%
DPQ070	with	Cotinine	0.374	132.35%	0.374	132.35%	0.00%
DPQ080	with	DPQ090	97.722	-35.38%	97.722	-35.38%	0.00%
DPQ080	with	FS	7.38	-36.53%	7.38	-36.53%	0.00%
DPQ080	with	Cotinine	13.865	-36.36%	13.865	-36.36%	0.00%
DPQ090	with	FS	79.372	-37.63%	79.372	-37.63%	0.00%
DPQ090	with	Cotinine	1.083	-82.46%	1.083	-82.46%	0.00%
Average change:				137.04%		136.99%	-38.96%

the ML estimation was 25.130, while the QML LM value was 0.904, a change of 2680%. The other LM value difference was the same as in the first models- adding cotinine to the Depression measurement model and showing 2.2% change.

After deletion of observations within this dataset, and subsequently imputed, the LM values from the same two variable combinations had substantial changes between the ML and QML model estimations, just as they had before. The value of regressing age on cotinine went from 18.677 from the model using ML to 0.778 when using QML (2301% change); the percent LM value change for adding cotinine to the Depression-measurement model was 1.98% as shown in Table 8.

The percent change between ML and QML with Satorra-Bentler correction was negligible under the complete case analyses of the first models at -0.09%. For the second pair of models including the survey design weightings, the average change between estimators was -45.38%. For the final pair of models, the percent change was -38.96%. In both instances when incorporating the survey design, with and without imputations, the QML estimation produced smaller LM values in their respective modifications indices.

The change in the modification indices from the original dataset was much less when using multiple imputations than when using the prior models (using the complete case dataset with complex survey design) with the average percent change being 137.035% and 136.99% for ML and QML respectively. This value may be less change from the first ML model's LM values, but there are significant changes between the complete cases using complex data and the current ones with the additional imputations. The average absolute difference among variables between the QML models using the

complex survey design, with and without the imputations, is 227%, with the average LM value being reduced by 192%.

A final note of this section should be that the Lagrange multiplier values that changed significantly within each pair of models were regression parameters that should not be allowed in the structural equation model. First, regressing age on cotinine would make this a non-recursive model, which is not the intent of the model. Secondly, adding cotinine to the latent variable Depression is not viable as it does not make theoretical sense, nor does it make empirical sense as it is not part of the validated depression screener.

4.8 Final Models

The next iteration of the model was produced to show the model fit indices, coefficients, and standard errors of the model using QML with the complete NHANES data using complex survey design and multiple imputation procedures. This model was produced in the same way as the previous QML model for comparison using the complete cases data with the complex survey design and imputations. The fit indices of this model are nearly the same. The Chi-square test is significant as the sample size is large. The RMSEA is 0.062 with the upper value of the 90% confident interval being less than 0.1. The SRMR 0.032 and the TLI and CFI are above 0.90, showing that this model is a relatively good fit to the data. Model-fit statistics are shown in Table 9, and Table 10 shows the coefficients and standard errors for the structural model. All paths were significant (p<0.001) in this model, as well as each previous model regardless of estimation method.

Comparing the estimates from this model, using the full NHANES dataset with multiple imputation, had a reasonably large change in coefficients compared to the first iteration of the model using ML with complete cases, and also to the fourth iteration using QML with complete cases adding the complex survey design. The average percent change for the coefficients from the first iteration was 6.25% with over 100% change for the standard errors. The average percent change from the fourth iteration was 13.36% for the coefficients and 21.30% for the standard errors.

The last iteration of the model accounted for the Lagrange multiplier values that were greater than 50 in the modification index from the first iteration by structuring covariances between those measurement model variables. The Satorra-Bentler correction for this model was lowered to 2.603. Adding the covariance structures increased the models' fit to the data, thereby effecting the model fit statistics. The TLI and CFI increased to 0.986 and 0.971 respectively. The SRMR decreased to 0.012, while the RMSEA decreased to 0.024, with the 90% confidence interval being 0.020 to 0.028. The AIC, BIC, and sample size adjusted BIC (659325.287, 659759.214, and 659581.249 respectively) were reduced, showing this is a better model with the covariances between DPQ variables added.

This final model (Figure 11) using the full NHANES dataset with complex survey design and multiple imputations indicated that age has a statistically significant influence on all other variables included in the model. With the addition of the covariances within the measurement model (i.e., Depression), the Lagrange Multiplier values within this modification index are attenuated. Table 12 shows unstandardized units of regression coefficients for the variables' relationships and shows that for each year of age, a

Table 9.

Fit Indices for Full NHANES Data with 30 imputations (N=17132, 153,038,278).

Iterations	90.000
Degrees Of Freedom	51.000
Satorra-Bentler Correction Factor	2.946
Chi-Square Test P Value:	<0.001
Loglikelihood (H0)	- 331142.123
Loglikelihood (H1)	- 329409.377
Number Of Free Parameters	37
Akaike Information Criteria (AIC)	662358.245
Bayesian Information Criteria(BIC)	662644.947
Sample-Size Adjusted Bayesian (BIC)	662527.363
RMSEA	0.062*
90% Confidence Interval	0.059 0.065
P-Value RMSEA <= 0.05	<0.001
SRMR	.032
Comparative Fit Index (CFI)	0.930*
Tucker-Lewis Index (TLI)	0.909*

* Denotes robust statistic for QML with Satorra-Bentler correction as produced by Lavaan package in R.

Table 10.

SEM estimates and standard errors using QML- Satorra-Bentler correction for the NHANES cycles 2005-10 (n=17132, N=153,038,278).

	Estimate	SE	z	*P*
Measurement Model (Standardized):				
Depression on				
DPQ010	0.6770	0.0120	57.2590	<0.001
DPQ020	0.7700	0.0070	107.8120	<0.001
DPQ030	0.5480	0.0100	55.3930	<0.001
DPQ040	0.6110	0.0090	65.8060	<0.001
DPQ050	0.5830	0.0100	57.7600	<0.001
DPQ060	0.6910	0.0100	69.3730	<0.001
DPQ070	0.6230	0.0110	57.5690	<0.001
DPQ080	0.5320	0.0140	36.9090	<0.001
DPQ090	0.4380	0.0150	28.6900	<0.001
Structural Model (Unstandardized):				
FS on Age	-0.0060	0.0010	-7.3330	<0.001
Cotinine on Age	-0.5440	0.0750	-7.2320	<0.001
Cotinine on FS	9.9180	1.4070	7.0490	<0.001
Depression on Age	-0.0020	0.0000	-4.0110	<0.001
Cotinine on Depression	11.1700	1.1280	9.9020	<0.001
Depression on FS	0.1660	0.0110	15.1430	<0.001
Variances (Unstandardized):				
DPQ010	0.234	0.009	25.420	<0.001
DPQ020	0.179	0.007	26.810	<0.001
DPQ030	0.590	0.016	37.445	<0.001
DPQ040	0.505	0.015	34.272	<0.001
DPQ050	0.348	0.011	31.230	<0.001
DPQ060	0.186	0.007	26.755	<0.001
DPQ070	0.230	0.008	27.312	<0.001
DPQ080	0.159	0.006	25.369	<0.001
DPQ090	0.059	0.005	12.948	<0.001
FS	1.785	0.127	14.060	<0.001
Cotinine	16680.716	739.710	22.550	<0.001

Table 11.

Modification Indices for the SEM of the NHANES dataset cycles 2005-2010 for participants > 20 years of age.

			QML with Full NHANES Data
			LM Value
Measurement model regressions			
Dep	by	Cotinine	140.993
Structural Regressions			
Dep	on	Cotinine	123.868
Age	on	Food Security	0
Age	on	Cotinine	1.381
Age	on	Dep	0
Covariances			
DPQ010	with	DPQ020	254.3
DPQ010	with	DPQ030	24.295
DPQ010	with	DPQ040	29.478
DPQ010	with	DPQ050	2.434
DPQ010	with	DPQ060	41.694
DPQ010	with	DPQ070	23.236
DPQ010	with	DPQ080	42.635
DPQ010	with	DPQ090	55.675
DPQ010	with	Food Security	11.759
DPQ010	with	Cotinine	4.044
DPQ020	with	DPQ030	124.716
DPQ020	with	DPQ040	128.722
DPQ020	with	DPQ050	188.489
DPQ020	with	DPQ060	475.61
DPQ020	with	DPQ070	37.764
DPQ020	with	DPQ080	92.771
DPQ020	with	DPQ090	70.875
DPQ020	with	Food Security	0.747
DPQ020	with	Cotinine	6.557
DPQ030	with	DPQ040	1143.935
DPQ030	with	DPQ050	132.615
DPQ030	with	DPQ060	131.62

Table 11 continued.

DPQ030	with	DPQ070	3.264
DPQ030	with	DPQ080	4.744
DPQ030	with	DPQ090	70.86
DPQ030	with	Food Security	0.32
DPQ030	with	Cotinine	10.934
DPQ040	with	DPQ050	317.17
DPQ040	with	DPQ060	302.89
DPQ040	with	DPQ070	0.069
DPQ040	with	DPQ080	19
DPQ040	with	DPQ090	266.231
DPQ040	with	Food Security	35.563
DPQ040	with	Cotinine	6.32
DPQ050	with	DPQ060	26.203
DPQ050	with	DPQ070	0.439
DPQ050	with	DPQ080	2.482
DPQ050	with	DPQ090	77.869
DPQ050	with	Food Security	2.769
DPQ050	with	Cotinine	0.124
DPQ060	with	DPQ070	0.677
DPQ060	with	DPQ080	0.184
DPQ060	with	DPQ090	169.979
DPQ060	with	Food Security	4.036
DPQ060	with	Cotinine	0.941
DPQ070	with	DPQ080	315.326
DPQ070	with	DPQ090	1.005
DPQ070	with	Food Security	5.813
DPQ070	with	Cotinine	0.482
DPQ080	with	DPQ090	112.588
DPQ080	with	Food Security	11.547
DPQ080	with	Cotinine	17.537
DPQ090	with	Food Security	127.697
DPQ090	with	Cotinine	1.411

Table 12.

Final adjusted SEM model unstandardized coefficients and standard errors using QML-Satorra-Bentler correction for the NHANES cycles 2005-10 (n=17132, N=153,038,278).

	Estimate	SE	z	*P*
Measurement Model:				
Depression on				
DPQ010	0.425	0.012	55.242	<0.001
DPQ020	0.483	0.012	49.53	<0.001
DPQ030	0.478	0.014	40.028	<0.001
DPQ040	0.546	0.012	48.576	<0.001
DPQ050	0.415	0.011	56.587	<0.001
DPQ060	0.396	0.011	54.356	<0.001
DPQ070	0.368	0.012	50.414	<0.001
DPQ080	0.238	0.011	34.862	<0.001
DPQ090	0.123	0.01	21.413	<0.001
Structural Model:				
FS on Age	-0.005	0.001	-7.333	<0.001
Cotinine on Age	-0.565	0.078	-7.232	<0.001
Cotinine on FS	9.171	1.464	7.049	<0.001
Depression on Age	-0.002	0.000	-4.011	<0.001
Cotinine on Depression	11.818	1.260	9.902	<0.001
Depression on FS	0.169	0.011	15.143	<0.001
Variances:				
DPQ010	0.234	0.009	25.420	<0.001
DPQ020	0.179	0.007	26.810	<0.001
DPQ030	0.590	0.016	37.445	<0.001
DPQ040	0.505	0.015	34.272	<0.001
DPQ050	0.348	0.011	31.230	<0.001
DPQ060	0.186	0.007	26.755	<0.001
DPQ070	0.230	0.008	27.312	<0.001
DPQ080	0.159	0.006	25.369	<0.001
DPQ090	0.059	0.005	12.948	<0.001
FS	1.785	0.127	14.060	<0.001
Cotinine	16680.716	739.710	22.550	<0.001

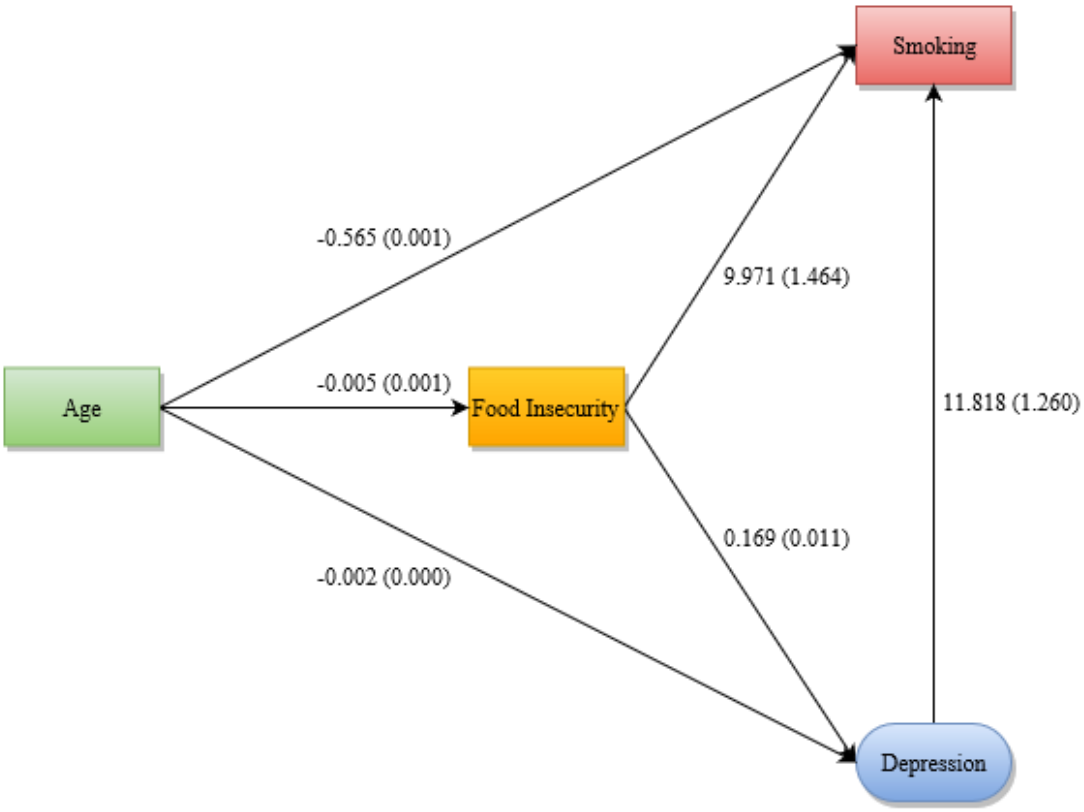

Figure 11. Final adjusted structural equation model of the effects of aging on smoking levels with mediating factors of food security and depression using QML estimation with Satorra-Bentler correction with the NHANES data (n=17132, N=153,038,278).

person's food insecurity score is reduced by 0.005. In turn, for each point reduction in food insecurity score, a person's serum cotinine will be on average 9.171 nanograms per milliliter (ng/ml) of blood lower. The total effect of a one-year increase in age will result in a decrease of serum cotinine of 0.644 ng/ml of blood; however, reducing depression has a far greater effect on cotinine levels, reducing it by 11.818ng/ml for every one unit decrease in this latent construct. Further, reducing food insecurity may play the greatest role in reducing smoking, as the collective effect would include an indirect path through depression resulting in a cumulative reduction of cotinine by 11.968 ng/ml.

CHAPTER V

DISCUSSION

This study set out to evaluate model fit and modification indices using quasi-maximum likelihood estimation with Satorra-Bentler correction in structural equation modeling using complex survey data. This study had aims to explore how coefficients, standard errors and goodness-of-fit tests differ under ML and QML estimators. Further, and as novel contributions to the literature, the research aimed to determine if there are differences in modification indices between estimators and whether multiple imputation is effective in the presence of missing data.

5.1 Hypotheses of the Study Revisited

The hypotheses for the study were that 1) QML estimation with Satorra-Bentler correction would improve the goodness-of-fit tests under increased data complexity, while 2) modification indices would show little if any change between ML and QML with each model pair, and 3) that the increase in standard errors that occurs from missing data and subsequent multiple imputation under complex survey design would be lessened in the presence of the QML with the Satorra-Bentler correction versus ML.

The National Health and Nutrition Examination Survey provided the necessary circumstances to demonstrate and analyze an SEM model with ML and QML estimators under complex design and multiple imputation as an empirical examples and a final model that is generalizable to the US population. The variables of age, food security status, depression, and cotinine as a measure of smoking, allowed a comparison of coefficients, standard errors, and Lagrange multiplier values from different types of variable distributions and ranges among the SEM iterations. The DPQ scale has been validated as a measure of depression, and literature has shown directional links between each of the components in the model.

Three model pairs were created under differing data situations to compare maximum likelihood and quasi-maximum likelihood with Satorra-Bentler correction. The first pair used complete case data without the NHANES survey design, while the second pair included it. The third pair was used with the same dataset that had been modified to include missing information that reflected the missingness in the full dataset. The final model used the full NHANES dataset, merged from cycles 2005 to 2010 with missing observations, utilizing multiple imputation and quasi-maximum likelihood with Satorra-Bentler correction. This last iteration represents a "best practice" approach to using large sample, complex survey design for generalization to the public.

First, by analyzing the patterns of missing data from NHANES, the study was later able to incorporate this pattern into the models and impute observations to mimic the procedures that are suggested to analyze large data and make generalizations. The first four models were analyzed using complete case analysis, whereas the first two did not apply the survey design, but the second two did.

The first two iterations used the NHANES data as a simple random sample and applied ML and QML with Satorra-Bentler correction. The next two models added the complex survey design, and the last two models incorporated the missingness and used multiple imputation to account for it. Comparisons of each model were then calculated based on absolute changes between competing estimators and modeled data complexity.

Comparisons of model fit indices between the maximum liklihood estimator and quasi-maximum likelihood with Satorra-Bentler correction had similar differences among each pair of models tested. The difference in the number of free parameters (11) resulted in the similarities in Akaikes Information Criterion and Bayesian Information Criterion with and without sample size adjustements between each pair of ML and QML models. These values show that the models using ML were lower between pairs and increase with the complexity of the datasets. For all models tested, the Chi square test was significant regardless of estimator used; however, because this test is sensitive to the large sample size other indices of fit were examined. A comparison of all model fit tests and indices is shown in Table 4.

The root mean square error of approximation was 0.01-0.02 points lower in the QML estimation than the ML models. This is meaningful because a lower value signifies a better fit. The 90% confidence interval was wider, though the increase in spread was to the lower end on all QML estimations versus their ML counterpart. The Standardized Root Mean Square Residual followed the same pattern as the RMSEA between model pairs and was 0.02-0.03 points lower in the QML models, also indicating better model fit. The Comparative Fit Index (CFI) and Tucker-Lewis Index (TLI) were both higher in the QML models. The CFI was 0.02-0.03 higher, and the TLI was 0.03-0.04 points higher.

The QML models' incremental fit indices also show a better fit compared to the null model.

Between ML and QML estimations at each level of data complexity, the coefficients were identical as shown in Table 5. QML with the Satorra-Bentler correction is supposed to account for the increased variance in the model due to non-normality and data complexity and thereby give a larger standard error. The average increase of standard error in the variables between ML and QML using the complete case dataset was just below 94%. The standard error increases were greater when applying the complex survey design, where the average increase was 154.26%.

The first hypothesis set for this study was supported in that the goodness-of-fit indices would have more acceptable values and therefore have lower rejection rates with quasi-maximum likelihood estimation with Satorra-Bentler correction under the conditions of increased data complexity versus the maximum likelihood estimation. This held true under all three pairs of models analyzed.

The second hypothesis held that there would be little if any change in the Lagrange Multiplier values of the modification under the same data complexity between maximum likelihood and quasi-maximum likelihood with Satorra-Bentler correction which the analyses showed; however, it is of note that there is a large discrepancy between using or not using the survey design- a gap that shows the imperativeness of using sampling weights. The changes that occurred in the modification indices were consistently in the regression of measurement and structural components, with the largest change coming in variables with the largest ranges. Among the Lagrange multiplier

values of the covariances from the modification indices, only one registered a difference: the 0.11% change the initial analyses comparing ML and QML without using complex survey design between DPQ040 and DPQ080 (highlighted in Table 6).

The third hypothesis was also supported. The coefficients remained relatively the same when using the complex survey design and adding imputations of the data compared to the complete case analysis, so that on average they were only about seven percent different from the coefficients produced from the complete case analysis. The average percent change in standard errors between using the complex survey design and adding imputations was less than one percent under each respective estimator, showing the effectiveness of imputations in the model and just over two percent change in all components of the model. The relatively large change in coefficients in the final model using the full NHANES data from the complete case analysis highlights the importance of using the full dataset. Complete case analysis should only be used with data that can be verifiably missing completely at random and only when relatively small amounts of data are missing.

The final model shows that as a person's age increases, levels of cotinine decrease. The amount of decrease through age alone may be statistically significant, but may not be practically significant. The cumulative reduction in cotinine per one year increase in age was 0.644 ng/ml, which may take a light smoker with 10ng/ml serum cotinine nearly 15 years to reduce to undetectable levels. From the model presented in Figure 11, reducing food insecurity would produce the greatest cumulative effect reduction in cotinine. For a one-point reduction in scoring on the Food Security Survey Module, there would be a reduction of 11.968 ng/ml of cotinine combining food

insecurity's direct effect combined with the indirect effect of reducing depression. Therefore, targeted interventions on younger adults experiencing food insecurity or depression, or both, may have the greatest effect on smoking behavior.

5.2 Limitations

A potential limitation of this study is the finite number of models that were conducted in this study. The variables in the study were chosen deliberately both to meet the theoretical pathway assumptions necessary for a SEM and to represent varying sizes of ranges and non-normality. However, the variables included are only a subset of possible types of variables that could be included in SEM and collected through surveys. Although using complex survey design with NHANES data should be generalizable to the population, it may be biased based on the sample selection, regardless of the use of weightings; therefore invariance testing may be appropriate for future research. Additionally, while the model tested herein is theoretically supported by literature, another consideration is that older adults who smoke were not available to complete the NHANES survey.

5.3 Recommendations

Additional research assessing models with variables of differing ranges, in addition to categorical variables, should be evaluated to determine the extent of change between estimation methods on modification indices, coefficients, standard errors, and goodness-of-fit statistics. Another future research endeavor may use invariance testing between these NHANES cycles to determine reliability of the model and of the NHANES data with survey design and sampling weights over time.

5.4 Conclusions

This study was conducted to evaluate quasi-maximum likelihood estimation with Satorra-Bentler correction in structural equation modeling with complex sampling design using the National Health and Nutrition Examination and Survey data. Variables were chosen specifically to have normal and non-normal distributions with varying ranges to identify areas of poorest fit. Goodness-of-fit statistics, coefficients, standard errors, and modification indices were compared against a maximum likelihood estimation with matching conditions of complete cases analysis without and with complex survey design and then with multiple imputation. A final model was completed using best practices of SEM using QML with Satorra-Bentler correction and multiple imputation using the full NHANES dataset, consisting of three cycles of surveys and examinations from 2005-2010.

Results of this study indicate that in all iterations paired under the same data complexity, the QML estimation with Satorra-Bentler correction produced better goodness-of-fit statistics. QML produced appropriately higher standard error values than the ML counterpart due to the non-normally distributed variables, while the coefficient values remained the same between pairs. Further, findings from this study show that there were differences in modification indices between estimation techniques, however, the differences of note were between variables that would not be useful in model respecification.

REFERENCES

Arene, C. J., & Anyaeji, R. C. (2010). Determinants of food security among households in Nsukka Metropolis of Enugu State, Nigeria. *Pakistan Journal of Social Sciences*, *30*(1), 9-16.

Armour, B. S., Pitts, M. M., & Lee, C. W. (2008). Cigarette smoking and food insecurity among low-income families in the United States, 2001. *American journal of health promotion*, *22*(6), 386-390.

Andridge, R. R., & Little, R. J. (2010). A review of hot deck imputation for survey non-response. International statistical review, 78(1), 40-64.

Bentler, P. M. (1990). Comparative fit indexes in structural models. Psychological bulletin, 107(2), 238.

Bentler, P. M., & Bonett, D. G. (1980). Significance tests and goodness-of-fit in the analysis of covariance structures. Psychological bulletin, 88(3), 588.

Bollen, K. A., Tueller, S. J., & Oberski, D. (2013). Issues in the structural equation modeling of complex survey data. In *Proceedings of the 59th World Statistics Congress*.

Bodner, Todd E. (2008) “What improves with increased missing data imputations?” Structural Equation Modeling: A Multidisciplinary Journal 15: 651-675.

Breslau, N., & Peterson, E. L. (1996). Smoking cessation in young adults: age at initiation of cigarette smoking and other suspected influences. *American journal of public health*, *86*(2), 214-220.

Carroll, R. J., Ruppert, D., Stefanski, L. A., & Crainiceanu, C. M. (2006). Measurement error in nonlinear models: a modern perspective. CRC press.Carter, K. N., Kruse, K., Blakely, T., & Collings, S. (2011). The association of food security with psychological distress in New Zealand and any gender differences. Social Science & Medicine, 72(9), 1463-1471. doi:10.1016/j.socscimed.2011.03.009

Carter, K. N., Kruse, K., Blakely, T., & Collings, S. (2011). The association of food security with psychological distress in New Zealand and any gender differences. *Social Science & Medicine*, 72(9), 1463-1471. doi:10.1016/j.socscimed.2011.03.009

Centers for Disease Control and Prevention. (2006). National Center for Health Statistics (NCHS). National Health and Nutrition Examination Survey Data. Hyattsville, MD: U.S. Department of Health and Human Services, Centers for Disease Control and Prevention, 2005-10. https://wwwn.cdc.gov/nchs/nhanes/continuousnhanes/default.aspx?BeginYear=2005.

Centers for Disease Control and Prevention (2006). National Center for Health Statistics (NCHS). National Health and Nutrition Examination Survey Questionnaire and

Examination Protocol. Hyattsville, MD: U.S. Department of Health and Human Services, Centers for Disease Control and Prevention, 2005-10. https://wwwn.cdc.gov/nchs/nhanes/continuousnhanes/questionnaires.aspx?BeginYear=2005

Centers for Disease Control and Prevention (CDC. (2011). Quitting smoking among adults--United States, 2001-2010. *MMWR. Morbidity and mortality weekly report*, *60*(44), 1513.

Coleman-Jensen, A., Rabbitt, M., Gregory, C., Singh, A. (2015). Household food security in the United States, 2014. Retrieved from USDA Economic Research Service.

De Marco, M., Thorburn, S., & Kue, J. (2009). "In a country as affluent as America, people should be eating": Experiences with and perceptions of food insecurity among rural and urban Oregonians. *Qualitative Health Research*, 19(7), 1010-1024. doi:10.1177/1049732309338868.

Food and Agriculture Organization of the United Nations (FAO). (2009). The state of food insecurity in the world: Economic crises and lessons learned, 2009. Rome.

Ferron, J. M., & Hess, M. R. (2007). Estimation in SEM: A concrete example.

Garson, G. D. (2015). Structural Equation Modeling. Statistical Associates. http://www.statisticalassociates.com/sem_p.pdf

Gelman, A., & Hill, J. (2006). Data analysis using regression and multilevel/hierarchical models. Cambridge university press.

Graham, J. W., Olchowski, A. E., & Gilreath, T. D. (2007). How many imputations are really needed? Some practical clarifications of multiple imputation theory. Prevention science, 8(3), 206-213.

Greenland, S., & Finkle, W. D. (1995). A critical look at methods for handling missing covariates in epidemiologic regression analyses. American journal of epidemiology, 142(12), 1255-1264.

Hu, L. T., & Bentler, P. M. (1999). Cutoff criteria for fit indexes in covariance structure analysis: Conventional criteria versus new alternatives. Structural equation modeling: a multidisciplinary journal, 6(1), 1-55.

Johnson, C. L., Paulose-Ram, R., Ogden, C. L., Carroll, M. D., Kruszan-Moran, D., Dohrmann, S. M., & Curtin, L. R. (2013). National health and nutrition examination survey. Analytic guidelines, 1999-2010.

Klein, A. G., & Muthén, B. O. (2006). Modeling heterogeneity of latent growth depending on initial status. *Journal of Educational and Behavioral Statistics*, *31*(4), 357-375.

Klein, A. G., & Muthén, B. O. (2007). Quasi-maximum likelihood estimation of structural equation models with multiple interaction and quadratic effects. Multivariate Behavioral Research, 42(4), 647-673.

Kline, R. B. (2016). *Methodology in the social sciences. Principles and practice of structural equation modeling (4th ed.).* New York, NY, US: Guilford Press.

Kowarik, A., & Templ, M. (2016). *VIM*: Visualization and Imputation. R Package. Journal of Statistical Software, 74(7), 1-16. doi:10.18637/jss.v074.i07

Li, P., Stuart, E. A., & Allison, D. B. (2015). Multiple imputation: a flexible tool for handling missing data. Jama, 314(18), 1966-1967.

Little R. J., Rubin D. (2002) Statistical Analysis With Missing Data. 2nd ed. Hoboken, NJ: Wiley Interscience.

Liu, J., Zhao, S. R., & Reyes, T. (2015). Neurological and epigenetic implications of nutritional deficiencies on psychopathology: conceptualization and review of evidence. *International Journal of Molecular Sciences*, 16(8), 18129-18148. doi:10.3390/ijms160818129

Liu, Y., & Brown, S. D. (2013). Comparison of five iterative imputation methods for multivariate classification. *Chemometrics and Intelligent Laboratory Systems*, *120*, 106-115.

Lumley, T. (2014). *mitools*: Tools for multiple imputation of missing data. R package version 2.3. https://CRAN.R-project.org/package=mitools

Lumley, T. (2017). *survey*: Analysis of Complex Survey Samples". R package version 3.32.

Mango, N., Zamasiya, B., Makate, C., Nyikahadzoi, K., & Siziba, S. (2014). Factors influencing household food security among smallholder farmers in the Mudzi district of Zimbabwe. *Development Southern Africa*, *31*(4), 625-640.

MacCallum, R. (1986). Specification searches in covariance structure modeling. Psychological bulletin, 100(1), 107.

Mehmetoglu, M., & Jakobsen, T. G. (2016). Applied statistics using Stata: a guide for the social sciences. Sage.

Moosbrugger, H., Schermelleh-Engel, K., Kelava, A., & Klein, A. G. (2009). Testing multiple nonlinear effects in structural equation modeling: A comparison of alternative estimation approaches. Structural equation modeling in educational research: Concepts and applications, 103-136.

Myung, I. J. (2003). Tutorial on maximum likelihood estimation. Journal of mathematical Psychology, 47(1), 90-100.

Oberski, D. (2014). *lavaan.survey*: An R Package for Complex Survey Analysis of Structural Equation Models. Journal of Statistical Software, 57(1), 1-27. URL http://www.jstatsoft.org/v57/i01/.

R Core Team (2017). R: A language and environment for statistical computing. R Foundation for Statistical Computing, Vienna, Austria. URL http://www.R-project.org/.

Raghunathan, T. E., Lepkowski, J. M., Van Hoewyk, J., & Solenberger, P. (2001). A multivariate technique for multiply imputing missing values using a sequence of regression models. Survey methodology, 27(1), 85-96.

Revelle, W. (2017) psych: Procedures for Personality and Psychological Research, Northwestern University, Evanston, Illinois, USA,

https://CRAN.R-project.org/package=psych Version = 1.7.8.

Rosseel,Y. (2012). *lavaan*: An R Package for Structural Equation Modeling. Journal of Statistical Software, 48(2), 1-36. URL http://www.jstatsoft.org/v48/i02/.

RStudio Team (2015). RStudio: Integrated Development for R. RStudio, Inc., Boston, MA URL http://www.rstudio.com/.

Rubin, D. B. (1987). Multiple imputation for nonresponse in surveys (Vol. 81). John Wiley & Sons.

Satorra, A., & Bentler, P. M. (1994). Corrections to test statistics and standard errors in covariance structure analysis.

Schafer, J. L. (1997). *Analysis of incomplete multivariate data*. CRC press.

Schafer, J. L., & Graham, J. W. (2002). Missing data: our view of the state of the art. *Psychological methods*, *7*(2), 147.

Seligman, H. K., Laraia, B. A., & Kushel, M. B. (2010). Food insecurity is associated with chronic disease among low-income NHANES participants. The Journal of Nutrition, 140(2), 304-310.

Siefert, K., Heflin, C. M., Corcoran, M. E., & Williams, D. R. (2004). Food insufficiency and physical and mental health in a longitudinal survey of welfare recipients. *Journal of Health and Social Behavior*, 45(2), 171-186. doi:10.1177/002214650404500204

Sijtsma, K., & Van der Ark, L. A. (2003). Investigation and treatment of missing item scores in test and questionnaire data. *Multivariate Behavioral Research, 38*(4), 505-528.

Silvia, E. S. M., & MacCallum, R. C. (1988). Some factors affecting the success of specification searches in covariance structure modeling. *Multivariate Behavioral Research, 23*(3), 297-326.

Slade, T. B., & Bharadwaj, R. S. (2010). A case of acute behavioral disturbance associated with vitamin b (12) deficiency. Primary Care Companion to The Journal of Clinical Psychiatry, 12(6), PCC.10l00968. doi:10.4088/PCC.10l00968oli

StataCorp (2015). Statistical Software: Release 14. College Station, TX: StataCorp LP.

Stuart E. (2015). Missing data procedures for psychosocial research [PowerPoint slides]. Retrieved from www.biostat.jhsph.edu/~dscharf/missingdatamatters/Stuart-SummerInstitute-2015-MissingData.pdf

Teo, T., & Khine, M. S. (2009). Modeling Educational Research: The way forward. *Structural Equation Modeling in Educational Research: Concepts and applications*.

US Department of Agriculture, Economic Research Service (2017). US Adult Food Security Survey Module. https://www.ers.usda.gov/media/8279/ad2012.pdf

Vach, W., & Blettner, M. (1991). Biased estimation of the odds ratio in case-control studies due to the use of ad hoc methods of correcting for missing values for confounding variables. American journal of epidemiology, 134(8), 895-907.

van Buuren, S., & Groothuis-Oudshoorn, K. (2011). *mice*: Multivariate Imputation by Chained Equations in R. Journal of Statistical Software, 45(3), 1-67. URL http://www.jstatsoft.org/v45/i03/.

Vartiainen, E., Seppälä, T., Lillsunde, P., & Puska, P. (2002). Validation of self reported smoking by serum cotinine measurement in a community-based study. Journal of Epidemiology & Community Health, 56(3), 167-170.

White, H. (1982). Maximum likelihood estimation of misspecified models. *Econometrica: Journal of the Econometric Society*, 1-25.

Zhou, D., Shah, T., Ali, S., Ahmad, W., Din, I. U., & Ilyas, A. (2017). Factors affecting household food security in rural northern hinterland of Pakistan. *Journal of the Saudi Society of Agricultural Sciences*.

APPENDICES

Appendix A

NHANES Variables used in this research

Variable ID	Description
SEQN	Respondent sequence number
RIAGENDR	Gender of respondent
RIDAGEYR	Best age in years of the sample person at time of HH screening. Individuals 85 and over are top-coded at 85 years of age.
RIDRETH1	Reported racial ethnicity
WTMEC2YR	Full Sample 2 Year MEC Exam Weight
SDMVPSU	Masked Variance Pseudo-PSU
SDMVSTRA	Masked Variance Pseudo-Stratum
FSQ032a	FSSM Item 1
FSQ032b	FSSM Item 2
FSQ032c	FSSM Item 3
FSQ041	FSSM Item 4
FSQ052	FSSM Item 5
FSQ061	FSSM Item 6
FSQ071	FSSM Item 7
FSQ081	FSSM Item 8
FSQ091	FSSM Item 9
FSQ102	FSSM Item 10
DPQ010	DPQ Item 1
DPQ020	DPQ Item 2
DPQ030	DPQ Item 3
DPQ040	DPQ Item 4
DPQ050	DPQ Item 5
DPQ060	DPQ Item 6
DPQ070	DPQ Item 7
DPQ080	DPQ Item 8
DPQ090	DPQ Item 9
LBXCOT	Serum Cotinine

Appendix B

FSSM Adult Food Security Measure

1. In the last 12 months, I/we worried whether my/our food would run out before I/we got money to buy more.
2. In the last 12 months, I/we bought just didn't last, and I/we didn't have money to get more.
3. In the last 12 months, I/we couldn't afford to eat balanced meals.
4. In the last 12 months, did you/you or other adults in your household ever cut the size of your meals or skip meals because there wasn't enough money for food?
5. [IF YES ABOVE, ASK] How often did this happen—almost every month, some months but not every month, or in only 1 or 2 months?
6. In the last 12 months, did you ever eat less than you felt you should because there wasn't enough money to buy food?
7. In the last 12 months, were you ever hungry but didn't eat because you couldn't afford enough food?
8. In the last 12 months, did you lose weight because you didn't have enough money for food?
9. In the last 12 months, did you or other adults in your household ever not eat for a whole day because there wasn't enough money for food?
10. [IF YES ABOVE, ASK] How often did this happen—almost every month, some months but not every month, or in only 1 or 2 months?

Appendix C

DPQ Depression Screener

1. [Over the last 2 weeks, how often have you been bothered by the following problems:] little interest or pleasure in doing things?
2. [Over the last 2 weeks, how often have you been bothered by the following problems:] feeling down, depressed, or hopeless?
3. [Over the last 2 weeks, how often have you been bothered by the following problems:] trouble falling or staying asleep, or sleeping too much?
4. [Over the last 2 weeks, how often have you been bothered by the following problems:] feeling tired or having little energy?
5. [Over the last 2 weeks, how often have you been bothered by the following problems:] poor appetite or overeating?
6. [Over the last 2 weeks, how often have you been bothered by the following problems:] feeling bad about yourself - or that you are a failure or have let yourself or your family down?
7. [Over the last 2 weeks, how often have you been bothered by the following problems:] trouble concentrating on things, such as reading the newspaper or watching TV?
8. [Over the last 2 weeks, how often have you been bothered by the following problems:] moving or speaking so slowly that other people could have noticed? Or the opposite - being so fidgety or restless that you have been moving around a lot more than usual?
9. [Over the last 2 weeks, how often have you been bothered by the following problems:] thoughts that you would be better off dead or of hurting yourself in some way?

Appendix D

List of variables non-weighted missingness (N=17132).

Variable	Present	Missing	% Missing
Gender	17132	0	0%
Age	17132	0	0%
Race	17132	0	0%
Cotinine	15532	1600	9.34%
DPQ 1	14791	2341	13.66%
DPQ 2	14806	2326	13.58%
DPQ 3	14806	2326	13.58%
DPQ 4	14804	2328	13.59%
DPQ 5	14809	2323	13.56%
DPQ 6	14792	2340	13.66%
DPQ 7	14803	2329	13.59%
DPQ 8	14794	2338	13.65%
DPQ 9	14798	2334	13.62%
FSSM	12797	4335	25.30%

.

Appendix E

Annotated R Code

```
#####################################################################
#Packages used in this study
install.packages("lavaan")
install.packages("lavaan.survey")
install.packages("mitools")
install.packages("survey")
install.packages("VIM")
install.packages("MVN")
install.packages("mice")
install.packages("psych")
library("MVN")
library("mice")
library("lavaan")
library("mitools")
library("lavaan.survey")
library("survey")
library("readr")
library("VIM")
library("psych")

#####################################################################
#Import NHANES Data With Age 20+
NH0510F <- read.csv("C:/NHANES/nh0510F.csv", header = TRUE,
      sep=",")

#Tabulate Missingness For Variables
na_count<-sapply(NH0510F, function(y)
      sum(length(which(is.na(y)))))
na_count <- data.frame(na_count)
present<-(nrow(NH0510F))-na_count
percent<-na_count/(nrow(NH0510F))
data.frame(na_count,present,percent)
celltotF<-(nrow(NH0510F)*ncol(NH0510F))
celltotF
mitotal<-sum(na_count)
mitotal
percentmi<-mitotal/celltotF
percentmi

#Create Unweighted Histograms figure. Highlight through "title"
get(getOption( "device" ) )()
par(mfrow = c(3, 4))
Age<-NH0510F$ridageyr
DPQ_1<-NH0510F$DPQ010
DPQ_2<-NH0510F$DPQ020
DPQ_3<-NH0510F$DPQ030
```

```
DPQ_4<-NH0510F$DPQ040
DPQ_5<-NH0510F$DPQ050
DPQ_6<-NH0510F$DPQ060
DPQ_7<-NH0510F$DPQ070
DPQ_8<-NH0510F$DPQ080
DPQ_9<-NH0510F$DPQ090
Food_Security<-NH0510F$fssm
Cotinine<-NH0510F$lbxcot

hist(Age, border="darkgreen", col="darkseagreen2", main="",
     breaks=8, xlim = c(20,90), freq = FALSE)
hist(DPQ_1, border="darkblue", col="lightblue", main="",
     breaks=5, xlim = c(0,3), freq = FALSE)
hist(DPQ_2, border="darkblue", col="lightblue", main="",
     breaks=5, xlim = c(0,3), freq = FALSE)
hist(DPQ_3, border="darkblue", col="lightblue", main="",
     breaks=5, xlim = c(0,3), freq = FALSE)
hist(DPQ_4, border="darkblue", col="lightblue", main="",
     breaks=5, xlim = c(0,3), freq = FALSE)
hist(DPQ_5, border="darkblue", col="lightblue", main="",
     breaks=5, xlim = c(0,3), freq = FALSE)
hist(DPQ_6, border="darkblue", col="lightblue", main="",
     breaks=5, xlim = c(0,3), freq = FALSE)
hist(DPQ_7, border="darkblue", col="lightblue", main="",
     breaks=5, xlim = c(0,3), freq = FALSE)
hist(DPQ_8, border="darkblue", col="lightblue", main="",
     breaks=5, xlim = c(0,3), freq = FALSE)
hist(DPQ_9, border="darkblue", col="lightblue", main="",
     breaks=5, freq = FALSE)
hist(Food_Security, border="goldenrod4", col="goldenrod2",
     main="", breaks=10, xlim = c(0,10), freq = FALSE)
hist(Cotinine, border="indianred4", col="lightcoral", main="",
     breaks=10, freq = FALSE)
title("Unweighted Variable Distributions", line=-2,cex.main = 2,
     font.main=6 , outer = TRUE)

#Create Survey Design And Weights
svydesign <- svydesign(ids = ~sdmvpsu, strata = ~sdmvstra,
     weights = ~wtmec6yr,nest = TRUE,
                       data = NH0510F)

#Create Weighted Histograms Figure. Highlight Through "Title..."
get( getOption( "device" ) )()
par(mfrow = c(3, 4))
svyhist(~Age, svydesign, border="darkgreen", col="darkseagreen2",
     main="", breaks=8, xlim = c(20,90), freq = FALSE)
svyhist(~DPQ_1, svydesign, border="darkblue", col="lightblue",
     main="", breaks=5, xlim = c(0,3), freq = FALSE)
svyhist(~DPQ_2, svydesign, border="darkblue", col="lightblue",
     main="", breaks=5, xlim = c(0,3), freq = FALSE)
```

```
svyhist(~DPQ_3, svydesign, border="darkblue", col="lightblue",
     main="", breaks=5, xlim = c(0,3), freq = FALSE)
svyhist(~DPQ_4, svydesign, border="darkblue", col="lightblue",
     main="", breaks=5, xlim = c(0,3), freq = FALSE)
svyhist(~DPQ_5, svydesign, border="darkblue", col="lightblue",
     main="", breaks=5, xlim = c(0,3), freq = FALSE)
svyhist(~DPQ_6, svydesign, border="darkblue", col="lightblue",
     main="", breaks=5, xlim = c(0,3), freq = FALSE)
svyhist(~DPQ_7, svydesign, border="darkblue", col="lightblue",
     main="", breaks=5, xlim = c(0,3), freq = FALSE)
svyhist(~DPQ_8, svydesign, border="darkblue", col="lightblue",
     main="", breaks=5, xlim = c(0,3), freq = FALSE)
svyhist(~DPQ_9, svydesign, border="darkblue", col="lightblue",
     main="", breaks=5, freq = FALSE)
svyhist(~Food_Security,  svydesign,border="goldenrod4",
     col="goldenrod2", main="", breaks=10, xlim = c(0,10), freq
     = FALSE)
svyhist(~Cotinine, svydesign,border="indianred4",
     col="lightcoral", main="", breaks=10, freq = FALSE)
title("Weighted Variable Distributions", line=-2,cex.main = 2,
     font.main=6 , outer = TRUE)

#Get Descriptives For Variables (Unweighted)
describe(NH0510F)

#Tabulate Gender Counts
tabulate(NH0510F$riagendr)
tabulate(NH0510F$riagendr)/nrow(NH0510F)

#Age Mean (Weighted)
svymean(~ridageyr, svydesign)

#Create Figure for Missing Information By Race
data.frame<-NH0510F
NHF<-NH0510F[,c("ridreth1","fssm","lbxcot","DPQ010")]
md.pattern(NHF)
get( getOption( "device" ) )()
par(mfrow = c(1, 1))
matrixplot(NHF, interactive = F, sortby = "ridreth1",xlab = "",
     ylab = "Missingness by Race", axes = TRUE,)

#Create Figure for Missing Data Combinations
NHF1<-NH0510F[,c("fssm","lbxcot","DPQ010")]
md.pattern(NHF1)
get( getOption( "device" ) )()
par(mfrow = c(1, 1))
aggr(NHF1, prop = T, numbers = T,combined = FALSE,
     col=c("lightblue", "lightcoral"), axes=TRUE,
     font=list(family="Times"))
title("Missing Data Combinations", line=-1, cex.main = 2,
     font.main=6 , outer = TRUE)
```

```
#####################################################################
#Import Complete Case NHANES Data
NH0510 <- read.csv("C:/NHANES/nh0510cc.csv", header = TRUE,
      sep=",")

#Tabulate Gender Counts
tabulate(NH0510$riagendr)
tabulate(NH0510$riagendr)/nrow(NH0510)

#Create CFA Model
CFAMODEL<-'
measurement model
Dep =~ DPQ010 + DPQ020 + DPQ030 + DPQ040 + DPQ050 + DPQ060 +
      DPQ070 + DPQ080 + DPQ090
'
CFADEP<-cfa(CFAMODEL, data=NH0510,
      control=list(init_nelder_mead=TRUE), verbose = TRUE,
      auto.var = TRUE, std.lv = TRUE,
            int.ov.free = TRUE, estimator = "MLM", mimic="MPLUS")
CFADEP
#Call Fit Statistics And Modification Indices
summary(CFADEP, fit.measures=TRUE, standardized=TRUE)
modificationIndices(CFADEP)

standardizedSolution(CFADEP, type = "std.all", se = TRUE,
                     zstat = TRUE, pvalue = TRUE, remove.eq =
      TRUE,
                     remove.ineq = TRUE, remove.def = FALSE,
                     GLIST = NULL, est = NULL)

#####################################################################
#Construct SEM Model
MODEL<-'
#measurement model
Dep =~ DPQ010 + DPQ020 + DPQ030 + DPQ040 + DPQ050 + DPQ060 +
      DPQ070 + DPQ080 + DPQ090
#regressions
fssm ~ ridageyr
lbxcot ~ ridageyr
lbxcot ~ fssm
Dep ~ ridageyr
lbxcot ~ Dep
Dep ~ fssm
'

#Estimate SEM Model with Maximum Likelihood
fitML<-lavaan(MODEL, data=NH0510, auto.var = TRUE, std.lv = TRUE,
              int.ov.free = TRUE, estimator = "ML")

#Call Fit Statistics And Modification Indices
```

```
standardizedSolution(fitML, type = "std.all", se = TRUE,
                     zstat = TRUE, pvalue = TRUE, remove.eq =
     FALSE,
                     remove.ineq = FALSE, remove.def = FALSE,
                     GLIST = NULL, est = NULL)
summary(fitML, fit.measures=TRUE, standardized=TRUE)
modificationIndices(fitML)

#Estimate SEM Model with Quasi-Maximum Likelihood & SB Correction
fitMLM<-lavaan(MODEL, data=NH0510, auto.var = TRUE, std.lv =
     TRUE,
               int.ov.free = TRUE, estimator = "MLM")
fitMLM

#Call Fit Statistics And Modification Indices
standardizedSolution(fitMLM, type = "std.all", se = TRUE,
                     zstat = TRUE, pvalue = TRUE, remove.eq =
     TRUE,
                     remove.ineq = TRUE, remove.def = FALSE,
                     GLIST = NULL, est = NULL)
summary(fitMLM, fit.measures=TRUE)
modificationIndices(fitMLM)

##################################################################
#SEM ML and QML Estimations-Complete Case & Complex Survey Design

#Create Survey Design And Weights
svydesign <- svydesign(ids = ~sdmvpsu, strata = ~sdmvstra,
     weights = ~wtmec6yr,nest = TRUE,
                       data = NH0510)

#Use Lavaan.Survey-Combine Model And Survey Design Using ML
SURVEYML<-lavaan.survey(lavaan.fit = fitML, survey.design =
     svydesign, estimator = "ML")
SURVEYML
#Call Fit Statistics And Modification Indices
standardizedSolution(SURVEYML, type = "std.all", se = TRUE,
                     zstat = TRUE, pvalue = TRUE, remove.eq =
     TRUE,
                     remove.ineq = TRUE, remove.def = FALSE,
                     GLIST = NULL, est = NULL)
summary(SURVEYML, fit.measures=TRUE)
modificationIndices(SURVEYML)


#Use Lavaan.Survey-Combine Model And Survey Design Using QML
SURVEYMLM<-lavaan.survey(lavaan.fit = fitMLM, survey.design =
     svydesign, estimator = "MLM")
SURVEYMLM
```

```
#Call Fit Statistics And Modification Indices
standardizedSolution(SURVEYMLM, type = "std.all", se = TRUE,
                     zstat = TRUE, pvalue = TRUE, remove.eq =
     TRUE,
                     remove.ineq = TRUE, remove.def = FALSE,
                     GLIST = NULL, est = NULL)
summary(SURVEYMLM, fit.measures=TRUE)
modificationIndices(SURVEYMLM)

#################################################################
#Import NHANES Complete Case Data with Artificial Incompleteness

NH0510MI <- read.csv("C:/NHANES/nh0510MI.csv", header = TRUE,
     sep=",")

#Tabulate Missingness For Variables
na_count<-sapply(NH0510MI, function(y)
     sum(length(which(is.na(y)))))
na_count <- data.frame(na_count)
present<-(nrow(NH0510MI))-na_count
percent<-na_count/(nrow(NH0510MI))
data.frame(na_count,present,percent)
mitotal<-sum(na_count)
mitotal

data.frame<-NH0510MI
NHCCMiR<-data.frame[,c("ridreth1","fssm","lbxcot","DPQ010")]
md.pattern(NHCCMiR)

#Create Figure Of Missingness Information By Race
get( getOption( "device" ) )()
par(mfrow = c(1, 1))
matrixplot(NHCCMiR, interactive = F, sortby = "ridreth1",xlab =
     "", ylab = "Missingness by Race", axes = TRUE,)

#Create Figure for Missing Data Combinations
NHCCMiP<-data.frame[,c("fssm","lbxcot","DPQ010")]
md.pattern(NHCCMiP)
get( getOption( "device" ) )()
par(mfrow = c(1, 1))
aggr(NHCCMiP, prop = T, numbers = T,combined = FALSE,
     col=c("lightblue", "lightcoral"),gap=3,
     cex.axis=1,cex.numbers=1,
     axes=TRUE, font=list(family="Times"))

#Get Density Plot Trace Of Variables
get( getOption( "device" ) )()
par(mfrow = c(1, 1))
densityplot(NH.MI)

#Re-Construct SEM Model
```

```
MODEL<-'
#measurement model
Dep =~ DPQ010 + DPQ020 + DPQ030 + DPQ040 + DPQ050 + DPQ060 +
     DPQ070 + DPQ080 + DPQ090
#regressions
fssm ~ ridageyr
lbxcot ~ ridageyr
lbxcot ~ fssm
Dep ~ ridageyr
lbxcot ~ Dep
Dep ~ fssm
'

#Create Model Estimation Component for ML
fitML<-lavaan(MODEL, data=NH0510MI, auto.var = TRUE, std.lv =
     TRUE,
              int.ov.free = TRUE, estimator = "ML")

#Create Model Estimation Component for QML
fitMLM<-lavaan(MODEL, data=NH0510MI, auto.var = TRUE, std.lv =
     TRUE,
               int.ov.free = TRUE, estimator = "MLM")

#Create Imputations Of Data To Account For Missing Information
NH.MI <- mice(NH0510MI, m=5, diagnostics = TRUE,
              printFlag = TRUE, seed = 5, maxit = 5)

NH.implist <- lapply(seq(NH.MI$m),function(im) complete(NH.MI,
     im))
NH.implist <-imputationList(NH.implist)

#Re-Create Survey Design And Weights
svydesign <- svydesign(ids = ~sdmvpsu, strata = ~sdmvstra,
     weights = ~wtmec6yr,nest = TRUE,
                       data = NH.implist)

#Use Lavaan.Survey-Combine Model And Survey Design Using ML
SURVEYML.MI<-lavaan.survey(lavaan.fit = fitML, survey.design =
     svydesign, estimator = "ML")
SURVEYML.MI

#Call Fit Statistics And Modification Indices
standardizedSolution(SURVEYML.MI, type = "std.all", se = TRUE,
                     zstat = TRUE, pvalue = TRUE, remove.eq =
     TRUE,
                     remove.ineq = TRUE, remove.def = FALSE,
                     GLIST = NULL, est = NULL)
summary(SURVEYML.MI, fit.measures=TRUE)
modificationIndices(SURVEYML.MI)
```

```
#Use Lavaan.Survey-Combine Model And Survey Design Using QML
SURVEYMLM.MI<-lavaan.survey(lavaan.fit = fitMLM, survey.design =
      svydesign, estimator = "MLM")
SURVEYMLM.MI

#Call Fit Statistics And Modification Indices
standardizedSolution(SURVEYMLM.MI, type = "std.all", se = TRUE,
                     zstat = TRUE, pvalue = TRUE, remove.eq =
      TRUE,
                     remove.ineq = TRUE, remove.def = FALSE,
                     GLIST = NULL, est = NULL)
summary(SURVEYMLM.MI, fit.measures=TRUE)
modificationIndices(SURVEYMLM.MI)

#################################################################
#Import NHANES Full Data
NH0510MI <- read.csv("C:/NHANES/nh0510F.csv", header = TRUE,
      sep=",")

#Re-Construct SEM Model
MODEL<-'
#measurement model
Dep =~ DPQ010 + DPQ020 + DPQ030 + DPQ040 + DPQ050 + DPQ060 +
      DPQ070 + DPQ080 + DPQ090
#regressions
fssm ~ ridageyr
lbxcot ~ ridageyr
lbxcot ~ fssm
Dep ~ ridageyr
lbxcot ~ Dep
Dep ~ fssm
'

#Create Model Estimation Component for QML
fitMLM<-lavaan(MODEL, data=NH0510MI, auto.var = TRUE, std.lv =
      TRUE,
                int.ov.free = TRUE, estimator = "MLM")

#Create Imputations Of Data
NH.MI <- mice(NH0510MI, m=30, diagnostics = TRUE,
              printFlag = TRUE, seed = 5, maxit = 5)

NH.implist <- lapply(seq(NH.MI$m),function(im) complete(NH.MI,
      im))
NH.implist <-imputationList(NH.implist)

#Re-Create Survey Design And Weights
svydesign <- svydesign(ids = ~sdmvpsu, strata = ~sdmvstra,
      weights = ~wtmec6yr,nest = TRUE,
                       data = NH.implist)
```

```
#Use Lavaan.Survey-Combine Model And Survey Design Using QML
SURVEYMLM.MI<-lavaan.survey(lavaan.fit = fitMLM, survey.design =
      svydesign, estimator = "MLM")
SURVEYMLM.MI

#Call Fit Statistics And Modification Indices
standardizedSolution(SURVEYMLM.MI, type = "std.all", se = TRUE,
                     zstat = TRUE, pvalue = TRUE, remove.eq =
      TRUE,
                     remove.ineq = TRUE, remove.def = FALSE,
                     GLIST = NULL, est = NULL)
summary(SURVEYMLM.MI, fit.measures=TRUE)
modificationIndices(SURVEYMLM.MI)
############################################################
#FINAL SEM Model With Added Covariances From Modification Index

#Construct SEM Model With Added Covariances and Repeat From Above
MODEL<-'
#measurement model
Dep =~ DPQ010 + DPQ020 + DPQ030 + DPQ040 + DPQ050 + DPQ060 +
      DPQ070 + DPQ080 + DPQ090
#regressions
fssm ~ ridageyr
lbxcot ~ ridageyr
lbxcot ~ fssm
Dep ~ ridageyr
lbxcot ~ Dep
Dep ~ fssm
DPQ010 ~~          DPQ020
DPQ010 ~~          DPQ090
DPQ020 ~~          DPQ030
DPQ020 ~~          DPQ040
DPQ020 ~~          DPQ050
DPQ020 ~~          DPQ060
DPQ020 ~~          DPQ080
DPQ020 ~~          DPQ090
DPQ030 ~~          DPQ040
DPQ030 ~~          DPQ050
DPQ030 ~~          DPQ060
DPQ030 ~~          DPQ090
DPQ040 ~~          DPQ050
DPQ040 ~~          DPQ060
DPQ040 ~~          DPQ090
DPQ050 ~~          DPQ090
DPQ060 ~~          DPQ090
DPQ070 ~~          DPQ080
DPQ080 ~~          DPQ090
'
```

```
#Create Model Estimation Component for QML
fitMLM<-lavaan(MODEL, data=NH0510MI, auto.var = TRUE, std.lv =
      TRUE,
                int.ov.free = TRUE, estimator = "MLM")

#Use Imputations Of Data from Above

#Use Lavaan.Survey-Combine Model And Survey Design Using QML

SURVEYMLM.MI<-lavaan.survey(lavaan.fit = fitMLM, survey.design =
      svydesign, estimator = "MLM")
SURVEYMLM.MI

#Call Fit Statistics And Modification Indices
standardizedSolution(SURVEYMLM.MI, type = "std.all", se = TRUE,
                     zstat = TRUE, pvalue = TRUE, remove.eq =
      TRUE,
                     remove.ineq = TRUE, remove.def = FALSE,
                     GLIST = NULL, est = NULL)
summary(SURVEYMLM.MI, fit.measures=TRUE)
modificationIndices(SURVEYMLM.MI)

##################################################################
```

VITA

Micah Lynn Hartwell

Candidate for the Degree of

Doctor of Philosophy

Thesis: STRUCTURAL EQUATION MODELING USING COMPLEX SURVEY DATA: EVALUATING QUASI-MAXIMUM LIKELIHOOD ESTIMATION WITH SATORRA-BENTLER CORRECTION AND MULTIPLE IMPUTATION

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